INVESTIGATING NITROGEN AND IRRIGATION MANAGEMENT STRATEGIES TO IMPROVE AGRONOMIC AND ENVIRONMENTAL OUTCOMES FOR POTATO PRODUCTION

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ABSTRACT

Nitrogen [N] fertilizer and irrigation management practices are both critical factors for determining agronomic and environmental outcomes for potato [*Solanum tuberosum (L.)*] production. This dissertation was comprised of two overall objectives.

First, a small-plot experiment evaluating the effects of six N rate, source, and timing treatments and two irrigation rate treatments on tuber yield, quality, net profitability, nitrate leaching, residual soil nitrate, plant N uptake, N nutrition index [NNI], N uptake efficiency, N utilization efficiency [NUtE], N use efficiency [NUE], biomass, harvest index, biomass, and potential N losses for potato [cv. 'Russet Burbank'] were investigated in 2016 and 2017 at Becker, MN, on a Hubbard loamy sand. Conventional N fertilizer best management practices [BMPs] (270 kg N ha^{-1}) were compared to reduced N rate (180 kg N ha^{-1}), control N rate (45 kg N ha^{-1}), and a variable rate [VR] N treatment based on the N sufficiency index [NSI] approach using remote sensing. Irrigation treatments included a conventional rate (100%) based on the "checkbook" method and a reduced rate (85%). The VR treatment reduced N applied relative to the recommended rate by 22 and 44 kg N ha^{-1} in 2016 and 2017, respectively. Irrigation rate was reduced by 29 and 33 mm in 2016 and 2017, respectively. From an agronomic perspective, neither VR N nor reduced irrigation produced significant differences in tuber yield or net return compared to full rate treatments. From an environmental perspective, nitrate leaching losses varied between 2016 and 2017 with flow-weighted mean nitrate N concentrations of 5.6 and 12.8 mg N L^{-1}, respectively, and increased from 7.1 to 10.4 mg N L^{-1} as N rate increased from 45 to

270 kg N ha^{-1}. Despite reductions in N rate for the VR N treatment, there was no significant difference in nitrate leaching compared with the existing N best management practices (BMPs). However, reducing irrigation rate by 15% decreased nitrate leaching load by 17% through a reduction in percolation.

Second, an evaluation of the relationship between NUE, NNI, and their variation across genotype [G] x environment [E] effects was conducted. A novel theoretical relationship between NNI and NUtE was derived: at a constant NNI value, NUtE values increased non-linearly as biomass increased, and at an NNI value of 1.0 this relationship defines the critical N utilization efficiency curve [CNUtEC]. Subsequently, an evaluation of the variation in critical N concentration [$\%N_c$] was conducted using a hierarchical Bayesian framework to infer the critical N dilution curve [CNDC] across G x E effects observed from multiple experimental trials. This statistical method was able to quantify the uncertainty in $\%N_c$, which was used to directly compare CNDCs. Critical N concentration was found to significantly vary across the effect of E, and in some cases for G within E. Therefore, consideration of both NNI and NUE require explicit consideration of the uncertainty in and variation due to G x E effects for $\%N_c$.

Overall, the findings of this dissertation improve both the empirical and theoretical understanding of the impact of N fertilizer and irrigation management practices on agronomic and environmental outcomes for potato.

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BMP, best management practice; CR, controlled release; DAP, diammonium phosphate; GRVI, Green Ratio Vegetation Index; NDVI, Normalized Difference Vegetation Index; MSAVI2, Modified Soil Adjusted Vegetation Index 2; MTCI, MERIS terrestrial chlorophyll index; NSI, nitrogen sufficiency index; PCU, polymer-coated urea; SPRF, Sand Plain Research Farm; SR8, Simple Ratio 8; UAN, urea/ammonium nitrate; UAV, unmanned aerial vehicle; VR, variable rate; NUE, nitrogen use efficiency; NUpE, nitrogen uptake efficiency; NUtE, nitrogen utilization efficiency; NNI, nitrogen nutrition index; HI, harvest index; iPAR, intercepted photosynthetically active radiation; RUE, radiation use efficiency; LAI, leaf area index; EONR, economically optimal nitrogen rate; CNDC, critical nitrogen dilution curve; CNUC, critical nitrogen uptake curve; CNUtEC, critical nitrogen utilization efficiency curve; W, total dry weight plant biomass; Y, dry weight tuber yield; NLoss Potential, potential nitrogen losses; N_{Input}, total nitrogen inputs to soil; $N_{Initial\ Soil}$, initial soil inorganic nitrogen; N_{Seed}, nitrogen in seed tubers; $N_{Fertilizer}$, applied nitrogen fertilizer; $N_{Irrigation}$, irrigation supplied nitrogen; $N_{Precipitation}$, precipitation supplied nitrogen; $N_{Mineralization}$, soil nitrogen mineralization; N_{Output}, total nitrogen outputs from soil; $N_{Residual\ Soil}$, residual soil inorganic nitrogen; N_{Plant}, plant nitrogen uptake; $N_{Leaching}$, nitrate leaching; $\%N_{Plant}$, plant nitrogen concentration; $\%N_{Critical}$, critical plant nitrogen concentration; $N_{Critical}$, critical plant nitrogen content; $NUtE_{Critical}$, critical nitrogen utilization efficiency; $\Delta\%N_c$, difference in critical nitrogen concentration, $CNDC_{lo}$, lower boundary of critical nitrogen dilution curve; $CNDC_{up}$, upper boundary of critical nitrogen dilution curve; G, genotype; E, environment; M, management; ANOVA, analysis of variance

INTRODUCTION

Potato [*Solanum tuberosum* (L.)] is an important specialty crop grown in the Upper Midwest with a small geographic footprint of 94,000 ha but a large economic impact with a production value of $857 million per year across Minnesota, North Dakota, Wisconsin and Michigan (USDA NASS, 2013). Effective management of irrigation and nitrogen [N] applications is a critical component of potato production necessary to maximize yields and economic returns while preventing negative environmental impacts (Alva, 2010; Meisinger & Delgado, 2002; Quemada et al., 2013; Zebarth & Rosen, 2007).

ENVIRONMENTAL IMPACTS

Typical management practices for potato lead to conditions that are primed for driving nitrate leaching (Kraft & Stites, 2003; Shrestha et al., 2010; Zebarth & Rosen, 2007) and high rate of groundwater use (Nocco et al., 2017) leading to an outsized negative impact on the environment. Improving the irrigation and N management practices of potato producers is a key strategy to reduce nitrate leaching losses to groundwater and the overuse of groundwater resources (Alva, 2010; Meisinger & Delgado, 2002; Munoz et al., 2005; Quemada et al., 2013).

In general, scientists are observing an increasing trend in pollution caused by N fertilizer (Erisman et al., 2013) and the societal costs of N pollution are being more formally quantified and accounted for in decision making (Gourevitch et al., 2018; Nigon et al., 2019). Losses of reactive N to the environment have substantial societal costs, estimated at US$210 billion yr−1 in the United States alone (Sobota et al., 2015). Additionally, 1% of global annual energy consumption is used to produce synthetic N fertilizer (Snyder et al., 2009), and reactive N has important interactions with carbon cycling, nitrous oxide emissions, and climate change (Gruber & Galloway, 2008).

The agronomic management of N fertilizer and irrigation has a particular impact on drinking water quality. When N fertilizer is over-applied, when crops are grown on vulnerable soils, or under adverse weather and climate conditions, groundwater can be contaminated by nitrate leaching (Meisinger & Delgado, 2002). Similarly, improperly applied irrigation can drive percolation below the root zone and result in the leaching of nitrate into groundwater (Hergert, 1986; Martin et al., 1991; Quemada et al., 2013). Surficial sandy aquifers are susceptible to nitrate contamination (Adams, 2016; Best et al., 2015) and when contaminated with nitrate above the EPA designated maximum contamination limit [MCL] of 10 mg N/L, drinking water from these aquifers poses a human health risks (US EPA, 2009). The MCL for nitrate is often exceeded in areas with vulnerable soils and intensive agricultural activity (MDA, 2015; MDH, 2017). This creates a significant financial burden on rural municipalities and private well owners who are required to install and pay for treatment of their drinking water to reduce nitrate concentration to safe limits (Keeler et al., 2016). Removing nitrate from drinking water is expensive for private well owners, $130 – $360 per household per year, and public water suppliers, $59 – $2224 per household per year, with a total cost across Minnesota estimated at $6 million per year (Keeler et al., 2016; Lewandowski et al., 2008).

Reducing the environmental impact of agricultural production is a major social issue, important to food consumers and political interests. There is growing political pressure to regulate N fertilizer use in order to prevent the impacts of nitrate pollution on water quality and climate change (Ferguson, 2015; Kanter, 2018; Kanter & Searchinger, 2018; Kanter et al., 2017; Kanter et al., 2015; MDA, 2015, 2018; Richard et al., 2018; Van Grinsven et al., 2016; Velthof et al., 2014; Zhang et al., 2015). There is also increasing interest in developing government incentives (Christianson et al., 2018; Jordan et al., 2018) or supply chain sustainability programs (EDF, 2018) to promote more environmentally friendly N fertilizer management practices.

The environmental impact of irrigated agriculture on groundwater resources in the Upper Midwest states of Minnesota, Wisconsin, North Dakota, and Michigan has been and continues to be a major area of concern. In this region, many aquifers used for agriculture irrigation are linked to surface water resources and ecosystems, some of which are sensitive to and suffering negative impacts from groundwater depletion (Kraft et al., 2012; Watson et al., 2014). Consumption of groundwater for agricultural irrigation can alter the hydrology of groundwater-surface water systems (Watson et al., 2014). Seasonal pumping dynamics can temporarily reduce the discharge of groundwater to lakes and streams (Kraft et al., 2012) – this can adversely impact aquatic life (Poff et al., 1997) leading to surrounding lakes and streams to be listed as impaired under the Clean Water Act (MN DNR, 2017; MN EQB, 2015). This has led to novel legal and policy issues in this region over the negative impact of groundwater use for agricultural irrigation on surface water resources (Marcotty, 2017; MN DNR, 2016; Richmond, 2017).

NITROGEN MANAGEMENT

Nitrogen fertilizer applications are one of the most important management practices that affect potato yield (Zebarth & Rosen, 2007). Compared to other major crops (e.g., corn), both over-application and under-application of N fertilizer have equally detrimental impacts on potato yield (Duchenne et al., 1997; Dyson & Watson, 1971a; Kleinkopf et al., 1981; Millard & Marshall, 1986). Best management practices for potato recommend either a split-applications of N fertilizer or use of a controlled-release fertilizer product, with the optimal N rate and source varying by variety and geographic region (Franzen et al., 2018; Lang et al., 1999; Rosen & Bierman, 2008; Stark et al., 2004). Between years, however, optimal N fertilizer rates for potato can vary by 25% or more because of variations in soils, management, and climatic conditions (Parent et al., 2017). The economic incentive to optimize N applications in potato relates to maximizing revenue (i.e., yield and quality) rather than decreasing input costs (i.e., fertilizer), because the cost of N is relatively cheap compared to the sale price of potato (Wilson et al., 2009).

To mitigate this risk of yield loss, measurements of petiole nitrate concentration are widely used to determine the optimal rate of in-season N application (Franzen et al., 2018; Lang et al., 1999; Rosen & Bierman, 2008; Stark et al., 2004). With this method, plant tissue samples are collected by growers using standard methods, analyzed by analytical laboratories, and the need for in-season N fertilizer is determined by established sufficiency ranges (Rosen & Eliason, 2005; Westcott et al., 1991). Despite widespread adoption, however, this approach has been suggested to be an unreliable predictor of crop N status (MacKerron et al., 1995; Pavek et al., 2017). High coefficient of variation between measurements, poor spatial resolution due to high cost to collect samples, sensitivity to cultural management practices (i.e. irrigation, N source and timing, etc.), and lack of correlation with whole-plant crop N status are significant limitations to this approach (Goffart et al., 2008).

Remote sensing based methods have been suggested as an alternative to petiole nitrate measurements (Goffart et al., 2008), and remote sensing is generally regarded as one of the most important tools currently available to improve upon existing in-season N management practices (Mulla, 2013). When appropriately used, remote sensing should be able to prevent excess application of supplemental N by identifying the occurrence of crop N stress. Spectral data acquired during the growing season can be used to monitor crop N status because spectral characteristics of green vegetation change as leaf chlorophyll content changes, and N is closely related to chlorophyll in plant cell metabolism (Berger et al., 2020; Fu et al., 2021; Stroppiana et al., 2011). In a similar manner, green vegetation can be discriminated from stressed vegetation or from soil. Remote sensing has been effectively used in many crops to predict biophysical parameters that are related to crop N status, such as leaf area index, tissue N concentration, plant N uptake, and leaf chlorophyll content (Chen et al., 2010; Cohen et al., 2010; Haboudane et al., 2004; Haboudane et al., 2002; Haboudane et al., 2008; Lamb et al., 2002; Liu et al., 2021; Muñoz-Huerta et al., 2013; Nigon et al., 2020; Reyniers et al., 2006).

Previous work has found that bands in the green, red, red-edge, and near-infrared spectral regions are best able discriminate between the rates of N applied to potato (Jain et al., 2007). Other past studies have also identified vegetation indices [VIs] which are strongly correlated with canopy chlorophyll concentration (Clevers & Kooistra, 2012; Clevers et al., 2017; Kooistra & Clevers, 2016), and leaf N concentration (Jain et al., 2007; Nigon, 2012; Nigon et al., 2015; Nigon et al., 2014). This includes VIs such as Simple Ratio 8 [SR8] (Datt, 1998), MERIS Terrestrial Chlorophyll Index [MTCI] (Dash & Curran, 2004), and Green Ratio Vegetation Index [GRVI] (Sripada et al., 2006). Other vegetation indices that only compare red and near-infrared bands, such as the Normalized Difference Vegetation Index [NDVI] (Rouse et al., 1974) or Modified Adjusted Soil Vegetation Index 2 [MSAVI2] (Qi et al., 1994), are known to reach a plateau in maximum value and unable to detect differences in crop N status (i.e., saturate out) as crop biomass increases and canopy cover exceeds 90% (Barnes et al., 2000; Nigon et al., 2014). These VIs, known as structural indices, are more closely related to crop canopy cover than crop N status (Barnes et al., 2000; Bouman et al., 1992b; Haverkort et al., 1991; Hunt et al., 2017; Nigon et al., 2015; Zhou et al., 2018). Recently, more advanced machine learning methods have been developed to predict crop N status from spectral data to improve upon the conventional VI approach (Berger et al., 2020; Chlingaryan et al., 2018; Fu et al., 2021; Nigon et al., 2020).

Proximal sensors such as chlorophyll meters (e.g., SPAD-502 meter) or active-optical reflectance sensors (e.g., GreenSeeker) can be used in a similar manner as remote sensing imagery to determine crop N status (Bean et al., 2018a, 2018b; Goffart et al., 2008; Paiao et al., 2020; Paiao et al., 2021; Samborski et al., 2009; Tremblay et al., 2011). While chlorophyll meters are relatively easy to use to collect point-based measurements, and have been shown to be strongly correlated with leaf N concentration (Nigon et al., 2014; Parry et al., 2014), they have much lower spatial resolution than other approaches (Ali et al., 2017; Tremblay et al., 2011).

Using a VI that has proven to be correlated with crop N status and using a “well-fertilized” reference plot to normalize remote sensing observations has been suggested as a viable approach for use potato and other crops (Colaço & Bramley, 2018; Franzen et al., 2016; Nigon et al., 2014; Samborski et al., 2009; van Evert et al., 2012; Zhou et al., 2017b), and this approach is generally referred to as the N Sufficiency Index [NSI] (Blackmer & Schepers, 1995). However, the need for a reference strip in the NSI method is a major logistical limitation and could be difficult in scaling from plot- to field-scale applications. One concern is that the NSI method does not produce an absolute measurement of crop N status and relies on the relative relationships to the "well-fertilized" reference plot, which is problematic in two ways. First, establishment of a single or multiple reference plots in a production system may be logistically challenging to do. Second, because the optimal N rate may vary between years, fields, and location within a field (Colaço & Bramley, 2019; Colaço et al., 2021; Parent et al., 2017; Ransom et al., 2020; Ransom et al., 2021; Raun et al., 2017), the NSI approach may incidentally lead to either over- or under-fertilization even with a properly established reference plot. Using an approach to directly estimate crop N status in potato such as the N nutrition index [NNI] may improve prediction accuracy and make remote sensing information more useful (Nigon et al., 2015).

Nitrogen nutrition index is a diagnostic tool used to quantify crop N status based upon the theoretical understanding of the allometric relationship between crop biomass and N concentration necessary to maximize growth (i.e., critical N dilution curve [CNDC]) (Lemaire et al., 2008; Lemaire et al., 2019; Lemaire et al., 2021). As crop biomass increases, the marginal quantity of N necessary to maximize relative growth rate decreases (Gastal et al., 2015; Sadras & Lemaire, 2014). While the NNI framework has been rapidly growing in interest as a research tool (Chen et al., 2021), it is at present impractical for widespread use in production systems due to the high labor costs of plant sampling and high laboratory analysis costs (Bélanger et al., 2001a; Ben Abdallah et al., 2016). Remote sensing, however, has been suggested as a low-cost and accurate method to estimate NNI (Lu et al., 2017; Mistele & Schmidhalter, 2008) and promising results to directly predict NNI from remote and proximal spectral sensing have been previously demonstrated in potato (Morier et al., 2015; Peng et al., 2021) as well as for other crops (Cao et al., 2018; Cummings et al., 2021; Dong et al., 2021; Dordas, 2017; Fabbri et al., 2020; Lu et al., 2017; Wang et al., 2021).

Critical N dilution curves have successfully been developed for and applied to potato across various genotype [G] x environment [E] interactions (Bélanger et al., 2001a; Ben Abdallah et al., 2016; Duchenne et al., 1997; Giletto & Echeverría, 2015). However, recent studies have suggested further limitations with the NNI framework that could hinder development of a universally applicable crop N status diagnostic tool for potato based on remote sensing. This includes observations that critical N concentration can vary between cultivars of a given crop species (i.e., G) and/or across variable climate and soil conditions (i.e., E) (Ciampitti et al., 2021; Makowski et al., 2020; Yao et al., 2021), moving beyond previous conceptions that variation in critical N concentration only occurs result of differences in metabolic pathways (i.e., C3 vs. C4) (Greenwood et al., 1990). There has been limited evaluation of whether or not these variation in critical N concentration are the result of intrinsic physiological differences (i.e., differential biomass allocation to structural, metabolic, and storage tissues) (Giletto et al., 2020) or confounding artifacts of differences in statistical method used (Makowski et al., 2020).

Previous work by Gastal et al. (2015); Lemaire et al. (1996); Sadras and Lemaire (2014) has indicated that accounting for crop N status using the NNI approach is also necessary to interpret the relationship between N use efficiency [NUE] and agronomic or environmental outcomes. Agronomic response to N can also be interpreted using the NNI framework which is more generalizable than an interpretation either in terms of rates, source, or timing of N applied (i.e., 4Rs) or in terms of marginal economic return (i.e., economic optimum N rate) (Gastal et al., 2015; Lemaire & Meynard, 1997; Sadras & Lemaire, 2014). Additionally, previous studies have identified the connection between increasing NUE and reducing N losses to the environment (Alva et al., 2006; Delgado et al., 2002; Devienne-Barret et al., 2000; Sadras & Lemaire, 2014). Similar to the limitations for NNI, however, interpreting NUE is subject to properly accounting for G x E interactions in crop N status (Lemaire & Ciampitti, 2020).

IRRIGATION MANAGEMENT

Irrigation management is necessary for potato when grown in arid climates or grown on sandy soils with low available water holding capacity in humid climates due to sensitivity to water stress and shallow rooting system (Shock et al., 2007a). Two-thirds of the potato production in this Upper Midwest utilizes supplemental irrigation (USDA NASS, 2013) due to the common practice of growing potato on sandy soils with very low water holding capacity.

A small, but significant, fraction of total crop acres, 1% (ND) – 8% (MI), in the Upper Midwest are irrigated (USDA NASS, 2012) – when water sensitive crops, such as vegetables, are grown on sandy soils in humid climates, transient water stress can occur between precipitation events and can reduce yield quantity necessitating supplemental irrigation (Shock et al., 2007b). The area of irrigated agriculture in the Upper Midwest has been increasing by 18% (WI) – 45% (MI) over the past two decades (USDA NASS, 2012), increasing in volume by 50% (MN) over the past three decades (MN EQB, 2015), and is expanding into areas not previously under agricultural production (Marcotty, 2016).

Irrigation requirements, in any case, must be determined throughout the growing season to account for temporal variations in precipitation and crop water use (i.e. evapotranspiration) (Bjorneberg et al., 2017). The currently recommended irrigation scheduling method for this region is known as the "checkbook" method (Steele et al., 2010; Wright, 2002). However, most potato producers utilize simplified irrigation management methods including applying a fixed volume of water on a regular basis, initiating irrigation based on the soil "feel" method, or initiating irrigation based on visually observed crop water stress at uniform rate across a field (Pehrson et al., 2010; USDA NASS, 2013). Soil moisture balance calculations [SMBC], such as the "checkbook" are used less frequently by producers (Pehrson et al., 2010; USDA NASS, 2013), but are recommended for use by various University Extension Services (Curwen & Massie, 1984; King & Stark, 1997; Sanford & Panuska, 2015; Scherer & Steele, 2019; Vitosh, 1984; Wright, 2002). This method tracks inputs (i.e. precipitation and irrigation) and outputs (i.e. drainage and evapotranspiration) in the root zone to account for the current soil moisture status (Steele et al., 2010).

Many of the recommend SMBC use simplified estimations of crop evapotranspiration [ET_c] – these "checkbook" methods were developed in the 1970s and 1980s (Lundstrom & Stegman, 1977; Lundstrom & Stegman, 1988; Stegman, 1980) and were advantageous when computational complexity and the lack of observations of and ability to communicate weather data prohibited the feasible implementation of more complex SMBCs. However, without regular measurements of soil moisture content, the simplified ET_c values used in the "checkbook" method results in over-estimation of soil moisture deficit and over-application of irrigation (Laboski et al., 2001; Steele et al., 1997).

The marginal cost of applying irrigation in the Upper Midwest is relatively inexpensive compared to the value of potato production (Wilson et al., 2009). While the cost and availability of water for irrigation varies by geographic region and can be a major factor in the economics of potato production, gross returns for potato can be reduced significantly with reduction in irrigation rate (Alva, 2008). While even slight reductions in irrigation volume will produce a yield response in potato in arid climates (Shock et al., 1998), it is less likely that an equivalent reduction in irrigation will have a significant effect in humid climates (Nigon, 2012; Shae et al., 1999; Waddell et al., 1999). However, because the risk of reduced yield and gross revenue is very high for potato when irrigation is not applied at sufficient rates, there is a strong economic incentive to apply irrigation at rates above crop requirements (Shock et al., 1998).

When irrigation is based on an inaccurate or biased estimate of soil moisture content, the wrong rate of supplemental irrigation will be applied potentially resulting in excessive drainage or crop water stress (Bjorneberg et al., 2017). Excess irrigation can drive percolation below the root zone (Hergert, 1986; Martin et al., 1991; Quemada et al., 2013) and reduced volume of supplemental irrigation is a potential strategy to reduce water use and nitrate leaching in humid climates. By maintaining a deficit of soil water storage between irrigation events (e.g., reduced irrigation volume) while maintaining soil water content above the allowable depletion limit, there is an increased capacity within the soil to store water from precipitation without driving percolation below the root zone and subsequently reducing nitrate leaching (Waddell et al., 2000).

Inefficient irrigation management practices are not only harmful to the environment (Cambouris et al., 2014; Levidow et al., 2014). Over-irrigation can reduce N use efficiency and increase nitrate leaching, while under-irrigation can lower tuber yield and quality (Alva, 2008; Quemada et al., 2013; Shock et al., 2007a; Shrestha et al., 2010); both outcomes negatively impact the profitability of producers.

OBJECTIVES

This dissertation is comprised of four chapters investigating the relationships between agronomic and environmental outcomes for potato production resulting from N fertilizer and irrigation management. The first three chapters comprise the findings of a single small-plot experiment for potato evaluating irrigation and N fertilizer treatments representing both conventional BMPs and novel management practices. The impact of these treatments on agronomic outcomes (i.e., tuber yield and quality, net revenue, plant N uptake, N use efficiency, and crop N status) and environmental outcomes (i.e., nitrate leaching and residual soil N), and the relationship between these two factors, is considered in these three chapters. The fourth chapter considers a consolidated set of small-plot experiments across a range of varieties, locations, and N fertilizer treatments and evaluates the relationship between the NNI, NUE, and G x E interactions. While each chapter has independent objectives defined within, across all four chapters the following objectives were broadly considered.

The primary objective of this dissertation was to understand the relationships underlying potato response to N fertilizer with the goal of identifying both empirical and theoretical criteria to improve agronomic management and environmental outcomes. Initially, this focused on utilizing remote sensing techniques to directly quantify crop N status (i.e., NSI, NNI) and apply in-season N fertilizer based on this method; however, this investigation subsequently developed into an evaluation of the interpretation and applicability of the metrics used to quantify crop N status (i.e., NUE, NNI). In this manner, the four chapters of this dissertation starts with empirically evaluating the rate-response relationship between tuber yield and N fertilizer for a single small-plot experiment (i.e., Chapters 1, 2, and 3) and concludes on a theoretical evaluation of crop N status and NUE across G x E relationships and their relationship to maximizing agronomic production and minimize environmental impacts (i.e., Chapters 3 and 4). Chapters 1, 2, and 3 all consider only a single set of small-plot experimental data while Chapter 4 considers a separate set of data combined across multiple small-plot experiments.

The secondary objective of this dissertation was to assess the N fertilizer and irrigation BMPs for potato production in the Upper Midwest, both in the context of the existing BMPs as well as within the context of desired agronomic and environmental outcomes. This objective was addressed primarily in the context of the small-plot experiment (i.e., Chapters 1, 2, and 3) and relied on consideration of this experiment in the context of previous studies considering N fertilizer and irrigation BMPs. In particular, this objective focused on evaluating the relationship between nitrate leaching loss and the N fertilizer and irrigation BMPs.

CHAPTER 1 – EVALUATION OF VARIABLE RATE NITROGEN AND REDUCED IRRIGATION MANAGEMENT FOR POTATO PRODUCTION

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ABSTRACT

Availability of soil moisture and N are primary limiting factors for potato growth on sandy soils in humid climates. This study was conducted to determine whether tuber yield or net economic return were affected by variable rate (VR) N or reduced irrigation management, and to evaluate methods to detect crop N status including remote sensing, chlorophyll meter, and petiole sampling. The effects of six N rate, source, and timing treatments and two irrigation rate treatments on tuber yield, quality, and net profitability for potato [*Solanum tuberosum* (L.) 'Russet Burbank'] were investigated in 2016 and 2017 at Becker, MN, on a Hubbard loamy sand. A VR N treatment based on the N sufficiency index (NSI) approach using remote sensing was also tested. Irrigation treatments included a conventional rate (100%) and a reduced rate (85%). The VR treatment reduced N applied relative to the recommended rate by 22 and 44 kg N ha^{-1} in 2016 and 2017, respectively. Irrigation rate was reduced by 29 and 33 mm in 2016 and 2017, respectively. Neither VR N nor reduced irrigation produced significant differences in tuber yield or net return compared to full rate treatments. Using NSI, remote sensing was able to predict crop N status with comparable accuracy to petiole sampling while chlorophyll meter measurements were less sensitive to detecting crop N stress. Managing N using remote sensing and reducing irrigation rate are strategies that could be used on sandy soils in humid climates without having agronomic or economic impacts on potato production.

CORE IDEAS

- Nitrogen and irrigation applications are critical to optimize yield in potato.
- Crop nitrogen stress in potato can be monitored with remote sensing.
- Irrigation rate can be reduced by 15% without impacting yields in humid climates.
- Remote sensing can reduce nitrogen rate by 15% without impacting yield.
- Remote sensing could replace petiole sampling to manage in-season nitrogen.

INTRODUCTION

Potato [*Solanum tuberosum* (L.)] is an important specialty crop grown in the Upper Midwest with a small geographic footprint of 94,000 ha but a large economic impact with a production value of (USD) $857 million per year across Minnesota, North Dakota, Wisconsin, and Michigan (USDA NASS, 2013). Because potato has high a N requirement of 270 kg N ha^{-1} in this region, university guidelines suggest applying fertilizer either as slow-release products or in multiple split-application via fertigation to reduce the potential for losses of applied N (Rosen and Bierman, 2008). Two-thirds of the potato production in this region utilizes supplemental irrigation (USDA NASS, 2013) due to the sensitivity of potato to water stress (Shock et al., 2007b) and the common practice of growing potato on sandy soils with very low water holding capacity. Effective management of irrigation and N applications is a critical component of potato production under these conditions to maximize yields and economic returns (Alva, 2010; Meisinger and Delgado, 2002; Quemada et al., 2013; Zebarth and Rosen, 2007).

Split-applications of N during the tuber bulking period are scheduled based on estimated crop need or using diagnostic tools such as petiole nitrate concentration, or proximal sensing using hand-held chlorophyll meters (Gianquinto et al., 2004; Goffart et al., 2008; Olivier et al., 2006). New methods to schedule split-application of N in potato based on remote sensing have been previously suggested (Goffart et al., 2008; Nigon et al., 2015) and evaluated (van Evert et al., 2012). Remote sensing is generally regarded as one of the most important tools currently available to improve on existing in-season management practices (Mulla, 2013) and has been effectively used in many crops to predict biophysical parameters that are related to crop N status, such as leaf area index, tissue N concentration, and leaf chlorophyll content (Chen et al., 2010; Cohen et al., 2010; Haboudane et al., 2002, 2004, 2008; Lamb et al., 2002; Reyniers et al., 2006). Previous work has found that narrow bands in the green (560 nm), red (650 to 680 nm), red-edge (710 to 740 nm), and near-infrared (>760 nm) are best able discriminate between the rates of nitrogen applied to potato (Jain et al., 2007). Vegetation indices which use combinations of these bands, such as Simple Ratio 8 (SR8) (Datt, 1998), MERIS Terrestrial Chlorophyll Index (MTCI) (Dash and Curran, 2004), or Green Ratio Vegetation Index (GRVI) (Sripada et al., 2006), have also been shown to be strongly correlated with crop N status in potato (Nigon et al., 2014, 2015). Other vegetation indices which only compare red and near-infrared bands, such as the Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974) or Modified Adjusted Soil Vegetation Index 2 (MSAVI2) (Qi et al., 1994), are known to reach a plateau in maximum value and unable to detect differences in crop N status (i.e., saturate out) as crop biomass increases and canopy cover exceeds 90% (Barnes et al., 2000; Nigon et al., 2014). These vegetation indices, known as structural indices, are more closely related to crop canopy cover than crop N status (Barnes et al., 2000; Nigon et al., 2015; Bouman et al., 1992; Haverkort et al., 1991). Using a vegetation index that has proven to be correlated with crop N status and using a reference strip to normalize remote sensing observations has been suggested as a viable approach for use potato and other crops (Nigon et al., 2014; Samborski et al., 2009). When appropriately used, remote sensing should be able to prevent excess application of supplemental N by identifying the occurrence of crop N stress.

Water sensitive crops, such as vegetables grown on sandy soils in humid climates can be subjected to transient water stress that can occur between precipitation events necessitating supplemental irrigation (Shock et al., 2007a). While annual precipitation exceeds evapotranspiration in the Upper Midwest, potato requires supplemental irrigation to prevent transient water stress due to high rates of crop water use and low available water holding capacity on sandy soils. Irrigation is typically applied in this region using overhead sprinklers and producers use a variety of techniques to manage irrigation including soil moisture balance calculations, monitoring crop water stress, measuring soil moisture content, or regularly scheduled fixed-volume applications (USDA NASS, 2013). The currently recommended irrigation scheduling method for this region is known as the checkbook method, which uses simplified estimations of crop evapotranspiration and drainage below the root zone (Wright, 2002; Steele et al., 2010).

Excess irrigation can drive percolation below the root zone (Hergert, 1986; Martin et al., 1991; Quemada et al., 2013) and reduced volume of supplemental irrigation is a potential strategy to optimize applications in humid climates. By reducing the volume of each irrigation event, there is an increased capacity within the soil to store water from precipitation without driving percolation below the root zone. This strategy should reduce the volume of supplemental irrigation applied while reducing the amount of percolation. Waddell et al. (1999) found that increasing the limit of management allowable water depletion from 30% to 60% reduced annual irrigation volume by 19%, decreased percolation by 31%, and did not reduce tuber yield. However, Nigon (2012) observed that reducing irrigation by 41% significantly reduced tuber yield by 11%.

The primary objective of this study was to determine whether total tuber yield, quality, or economic return were affected by variable rate (VR) N based on remote sensing or by reduced rate of supplemental irrigation compared to conventional management practices.

Secondarily, this study compared measurements of in-season crop N status from ground-based narrowband proximal sensing, UAV-based broadband remote sensing, handheld chlorophyll meter, and petiole nitrate samples.

MATERIALS AND METHODS

EXPERIMENTAL CONDITIONS

A plot-scale field experiment was conducted in 2016–2017 on irrigated plots at the Sand Plain Research Farm (SPRF) in Becker, MN (45°23′ N, 93°53′ W). Mean temperature at this station is 7.1°C and mean annual precipitation is 809 mm (Arguez et al., 2010). The soil at this station was characterized as a Hubbard loamy sand (Sandy, mixed, frigid Entic Hapludolls) and excessively well-drained with low available water holding capacity of 0.098 cm cm^{-1} for 0 to 90 cm depth (Hansen and Giencke, 1988; USDA NRCS, 2013). Russet Burbank potato, a processing variety common to the region, was grown each year following a previous full season crop of rye [*Secale cereale* (L.)]. Pre-plant soil samples were collected using a 2.2 cm diameter soil probe (AMS Inc., American Falls, ID). Eight samples were collected from each experimental replicate at two depths, 0 to 15, and 0 to 60 cm, and composite samples for each depth and replicate were used for further analysis. Macronutrient concentrations, percent organic matter, and pH were determined from the 0 to 15 cm depth samples using standard methods (Nathan and Gelderman, 2015). Phosphorus concentration was determined using the Bray-P1 method (Frank et al., 1998), potassium concentration was determined using ammonium acetate extraction (Warncke and Brown, 1998), soil organic matter was determined using the loss on ignition method (Combs and Nathan, 1998), and pH was determined using a 1:1 soil/distilled water solution

(Peters et al., 2012) (Table 1). Inorganic N concentration, measured individually as nitrate N and ammonium N, was determined from the 0 to 60 cm depth samples using conductimetric analysis (Carlson et al., 1990) (Table 1-1). Apart from experimental N and irrigation treatments, all management and cultural practices were managed by the staff at the SPRF in accordance with conventional practices for the region (Egel, 2017) and other macronutrients were applied based on soil samples and university recommendations (Rosen, 2018). A weather station (Campbell Scientific, Logan, UT) located at the SPRF and 1 km away from experimental plots recorded measurements of precipitation, maximum and minimum temperature, solar radiation, relative humidity, and wind speed every hour.

The experimental design for this study was split-plot within a randomized complete block design with four replicates. Plots used each year were positioned in adjacent locations within the same field and were not used repeatedly between years. Irrigation rate and timing was the main plot treatment (with two treatments), and N rate, source, and timing was the subplot treatment (with six treatments). Each replicate was separated by a 15.2 m buffer of rye and irrigation blocks within replicates were separated by a 9.1 m buffer alley. Experimental plots were 6.4 m wide (seven rows of 0.9 m width) and 6.1 m long with an additional 1.5 m buffer for plots located at the edge of the irrigation block. A 3.1 m buffer separated subplots within main plots that were co-located in the same set of seven rows. Whole "B" seeds were planted on 22 Apr. 2016 and 29 Apr. 2017 with a 0.3 m spacing between seeds. Vines were killed with a mechanical flail mower on 14 Sept. 2016 and 13 Sept. 2017 and tubers were mechanically harvested from the fourth and fifth rows on 30 Sept. 2016 and 27 Sept. 2017. Samples of vine biomass were harvested by hand from the fourth and fifth rows immediately prior to mechanical termination.

Irrigation treatments included conventional irrigation rate (Conventional) based on the checkbook method (Steele et al., 2010; Wright, 2002) but without using soil moisture measurements as corrections, and reduced irrigation rate (Reduced) with the rate reduced by 15% relative to Conventional (Table 1-2). Irrigation was applied on a fixed schedule of every 2 to 3 d using a solid-set sprinkler system. Irrigation was applied 19 and 22 times in 2016 and 2017, respectively. On a given date of application, irrigation was applied to the Conventional plot at a rate determined by the checkbook method to refill the profile completely. For retrospective analysis, soil moisture content was estimated over the growing season using a soil water balance calculation (Steele et al., 1997) with estimates of crop evapotranspiration calculated from the weather station at the SPRF (Jensen and Allen, 2016).

The six N treatments (Table 1-3) included a 45 kg N ha^{-1} control treatment (Control), a split-applied urea treatment at rates of 180 kg N ha^{-1} (180 Split) and 270 kg N ha^{-1} (270 Split), a controlled release (CR) polymer-coated urea (PCU; Environmentally Smart Nitrogen [Nutrien Inc., Saskatoon, SK, Canada]) treatment at rates of 180 kg N ha^{-1} (180 CR) and 270 kg N ha^{-1} (270 CR), and a VR split-applied urea treatment (VR Split) based on remote sensing observations paired with the N sufficiency index (NSI) (Blackmer and Schepers, 1995; Peterson et al., 1993). For the VR Split treatment, 270 CR was chosen as the well-fertilized reference because it had previously been identified as a best management practice for N applications (Rosen and Bierman, 2008). Fertilizer at planting was diammonium phosphate (DAP) applied as a band 2 cm below and 3 cm to each side of tubers to all N-treatments at a rate of 45 kg N ha^{-1}. Emergence fertilizer was urea for the 180 Split, 270 Split, and VR Split and PCU for 180 CR and 270 CR. Treatments 180 Split and 270 Split received four scheduled post-hilling applications of liquid urea/ammonium nitrate (UAN) in the form of simulated fertigation using a tractor mounted sprayer immediately followed by irrigation on a 1- to 2-wk basis.

SAMPLING PROCEDURES

Repeated measurements of multispectral reflectance were collected from a ground-based narrowband proximal sensor (MSR–16R, CROPSCAN, Inc., Rochester, MN) and a UAV-based broadband remote sensor (GEMS Multispectral Sensor, Sentek Systems, Lakeville, MN). CROPSCAN collects data from 16 bandwidths of 10 nm (460, 510, 560, 610, 660, 680, 710, 720, 740, 760, 810, 870, 950, 1320, 1500, and 1700 nm) and GEMS collects data from four bandwidths of ~100 nm (450, 560, 610, and 810 nm). Reflectance measurements were collected with CROPSCAN on a weekly basis on 10 dates between 21 June and 24 Aug. 2016 and on 11 dates between 1 June and 23 Aug. 2017. Four reflectance measurements were collected from the edge of each plot at a height of 1.8 m, giving a diameter of view of approximately 0.9 m, and the average daily value for each plot was used in subsequent analysis. Reflectance measurements were collected with GEMS on a weekly basis on nine dates between 12 June and 23 Aug. 2016 and three dates between 2 July and 29 July 2017. Reflectance measurements were collected at a height of 50 m with a resolution of 3 cm, and data pre-processing to convert raw imagery to reflectance values based on calibrated reflectance panels was conducted with software provided by Sentek Systems.

The MTCI, which had previously been identified as best able to detect crop N status in potato (Nigon et al., 2015) was calculated using CROPSCAN measurements. This index uses narrowband measurements of reflectance in the red (676 nm), red edge (713 nm), and near-infrared (751 nm) spectral regions. Post-hilling fertilizer was applied to VR Split as UAN at a rate of 22 kg N ha^{-1} using the same simulated fertigation method as 180 Split and 270 Split when the NSI value of MTCI calculated from CROPSCAN was less than 0.95 prior to the scheduled application date (Table 1-4).

Additional vegetative indices including GRVI, SR8, NDVI, and MSAVI2 were also calculated for comparison to MTCI using data collected from both CROPSCAN and GEMS (Table 1-4). Simple Ratio 8 uses measurements of narrowband reflectance in the green (554 nm), red-edge (704 nm), and near-infrared (857 nm) spectral regions. Normalized Difference Vegetation Index, MSAVI2, and GRVI use measurements of broadband reflectance in the red (600– 690 nm), green (520– 600 nm), and near-infrared (750– 900 nm) spectral regions.

Petiole samples and measurements using a chlorophyll meter (SPAD-502, Spectrum Technologies, Aurora, IL) were collected five times in 2016 between 16 June and 3 Aug. and six times in 2017 between 14 June and 8 Aug. every 1–2 wk. Petiole samples were collected from the fourth leaf from the apex of the shoot for 20 plants in each plot using destructive sampling where all leaflets were stripped from the petiole and discarded. Samples were oven dried at 60°C, ground, and sieved to 2 mm and extracted in an aqueous solution prior to analysis of N concentration for nitrate N content using conductimetric analysis (Carlson et al., 1990). The SPAD-502 measurements were collected nondestructively from a single leaflet on the fourth leaf from the apex of the shoot for 20 plants in each plot. Within a plot, petiole and SPAD-502 samples were not necessarily collected from the same leaves or plants.

Vegetation indices calculated from CROPSCAN and GEMS, as well as from SPAD-502 measurements, were all normalized using the NSI approach previously described. Petiole samples were assessed using previously developed threshold concentrations (Rosen and Eliason, 2005). Estimates of crop N status from all methods were then numerically compared to observe concurrence and disagreement between each approach.

Harvested tubers were mechanically sorted into weight classes (0–85 g, 85–170 g, 170–284 g, 284–397 g, and >397 g) and graded (US No. 1 and No. 2) (USDA, 1997). A subsample of 25 harvested tubers was then evaluated for scab infection and hollow heart internal defects. Tuber specific gravity was evaluated using the weight in air/weight in water method (Dean, 1994). Response variables assessed include total tuber yield, US No. 1 yield, the ratio of tubers greater than 170 g, the incidence of hollow heart defects, and tuber specific gravity.

Economic Analysis

An economic analysis was conducted to determine differences in net returns between treatments. For gross revenue, a base price of \$207.53 Mg^{-1} for tuber yield greater than 85 g was used based on the average reported price for Minnesota from 2014 to 2016 (USDA NASS, 2017). Irrigation application costs were estimated at \$0.203 mm^{-1} (R. Faber, personal communication, 2018). Nitrogen fertilizer costs were estimated at \$0.89 kg N^{-1} for urea, \$1.02 kg N^{-1} for UAN (Quinn, 2017), and \$1.32 kg N^{-1} for PCU (Nutrien, 2018); application costs for N fertilizer were estimated at \$44 ha^{-1} application^{-1} for urea, \$12 ha^{-1} application^{-1} for UAN, and \$22 ha^{-1} application^{-1} for PCU (Wilson et al., 2009).

The cost of remote sensing was estimated at \$5 ha^{-1} yr^{-1} based on commercially available satellite imagery (Farmers Edge, 2018).

The cost of petiole sampling and analysis was estimated at \$25 ha^{-1} (Eborn, 2017; Agvise Laboratories, 2018). Ownership costs and other operating costs including seed, non-nitrogen fertilizer (including DAP), pesticides and chemicals, machinery, labor, sorting, and miscellaneous categories were estimated to be \$6,270 ha^{-1} for all treatments (Eborn, 2017). Net returns were estimated for each experimental treatment by subtracting the cost of fertilizer and irrigation and the overall ownership and operating costs from gross revenue.

Statistical Analysis

Statistical analysis was conducted using SAS PROC GLIMMIX (SAS Institute, 2013) to test the fixed effects of study year, irrigation treatment, N treatment, and their interactions. The overall significance and *a priori* non-orthogonal contrast comparisons for N treatments (Table 1-5) were conducted for each response variable with significance set at $P < 0.10$.

Results and Discussion

Remote Sensing and Variable Rate Nitrogen

Overall, NSI calculated using MTCI measured with CROPSCAN could identify differences between N treatments (Figure 1-1). Remote sensing measurements of VR Split taken prior to scheduled post-emergence fertilizer applications were below the 95% NSI threshold using MTCI on two dates in 2016 and two dates in 2017. Following these dates, 22 kg N ha^{-1} were subsequently applied to the VR Split treatment (Table 1-6). There was one exception – on the fourth application date in 2016 (27 July), fertilizer was applied to VR Split although the NSI value using MTCI was 96% (i.e., not less than 95%). The decision to apply fertilizer on this date was due to a lack of subsequent opportunities to apply N fertilizer, and it was expected that the NSI value would subsequently drop below 95% within a few days. In total, three post-emergence N-fertilizer applications were applied to VR Split in 2016. Relative to the 270 Split treatment, N fertilizer application rate for the VR Split treatment was reduced by 22 and 44 kg N ha^{-1} in 2016 and 2017, respectively.

METHODS TO DETECT NITROGEN STATUS

CROPSCAN was also able to detect crop N stress using NSI with GRVI and SR8 vegetation indices (Table 1-6). Green Ratio Vegetation Index is less sensitive than, and SR8 is more sensitive than MTCI at detecting crop N stress. However, CROPSCAN was not able to detect crop N stress using NSI with NDVI and MSAVI2 vegetation indices. These indices are known to saturate out as crop biomass and canopy cover increase, meaning that they become unable to detect differences in crop N status (Barnes et al., 2000; Nigon et al., 2015). Canopy cover was fully closed for the four spectral imagery collection dates each year of this study that were used to determine supplemental N fertilizer applications, leading to the poor performance of NDVI and MSAVI2 at detecting crop N stress.

GEMS was able to detect crop N stress using NSI with GRVI and did so with a lesser degree of sensitivity compared to CROPSCAN. Of the three dates in which CROPSCAN GRVI detected crop N stress, GEMS GRVI detected crop N stress on only one date. Similar to CROPSCAN, GEMS did not detect crop N stress with NDVI or MSAVI2. It is not clear where the reduced sensitivity in detecting crop N stress of GEMS compared to CROPSCAN originates from. While the vegetative indices for both CROPSCAN and GEMS are calculated using the same algorithm, the spectral bandwidths collected by each sensor differ. Similarly, the sensors collected data at different spatial resolutions and on different dates. Investigating the sources of these differences could be an important area of future research.

SPAD-502 was not sensitive to crop N stress at a threshold NSI value of 0.95 for either year of the study, differing somewhat from previous findings. Nigon et al. (2014) found that SPAD-502 was able to predict leaf N concentration in Russet Burbank potato equally as well as GRVI and that it also performed better than NDVI, Similarly, Nigon (2012) found that SPAD-502, depending on sampling date, was as good as or a better predictor of leaf N concentration than SR8 and NDVI. The present study, however, compares the prediction of crop N status using the NSI method to normalized measurements from remote sensing and SPAD-502, which is different from directly evaluating their relationship with N concentrations in plant tissue. While SPAD-502 can be a useful tool for accurately quantifying crop N status, it does not have the same degree of relative sensitivity that remote sensing indices such as MTCI or SR8 provide. SPAD-502 also provides a much coarser degree of spatial resolution compared to remote sensing, because it requires on-the-ground sampling. SPAD-502 within an NSI framework could be used in future studies if the NSI threshold is greater than 0.95 (e.g., 0.97), to account for this lower degree of sensitivity. Adopting an NSI based approach requires careful consideration of the well-fertilized reference and method to monitor crop N status used, to select an appropriate threshold value (Nigon et al., 2014).

Petiole nitrate concentration, after log-transformation, correlated well with estimates of crop N status from MTCI (R^2 = 0.64), GRVI (R^2 = 0.67), and correlated moderately well with SR8 (R^2 = 0.42) measured with CROPSCAN. The relationship between log-transformed petiole nitrate concentration and NDVI (R^2 = 0.30) and MSVAI2 (R^2 = 0.17) was not as strong as the other vegetation indices evaluated. Previous studies have found that MTCI, GRVI, and SR8 are strongly correlated with leaf N concentration (Nigon et al., 2014, 2015), further confirming the findings of this study. Additionally, there were no discrepancies between supplemental N fertilizer application decisions that would have been made using petioles versus the decisions that were made using remote sensing. Remote sensing, therefore, has the potential to supplement or replace the widespread utilization of petiole nitrate sampling because it provides a similar degree of information on crop N status at a similar cost to collect and analyze samples with far greater spatial and temporal resolution. However, detecting crop N stress with remote sensing is still limited by the need for a reference strip. The NSI approach used in this study only can detect relative differences in N status. If a reference strip is not representative of N sufficiency because of poor choice in location or because of large spatial variability in N response throughout a field, then NSI method will fail to detect crop N stress accurately. Further, if reference strips are prohibitively difficult to adopt in a production or research setting, then petioles would be the best method to determine crop N status. Future work should be directed toward developing a method to determine crop N status from remote sensing data without the need for a reference strip such as the N nutrition index (Ben Abdallah et al., 2016; Lu et al., 2017).

SOIL MOISTURE CONTENT AND WATER BALANCE

The irrigation treatments had similar soil moisture deficits except for slight differences observed in June 2016 and July 2017 (Figure 1-2). Three factors were likely the source of the limited magnitude and temporal occurrence of differences in soil moisture deficit between treatments. First, the difference between irrigation application rates for the two treatments of 15% was relatively small. A more substantial reduction (e.g., 30%) in irrigation rate would likely increase the soil moisture deficit more noticeably. Second, the differences in soil moisture deficit occurred during periods of limited precipitation. Both years of this study had relatively high rates of precipitation, although there were occasional drier periods of 1 to 2 wk in which irrigation was the predominant input of water into the soil. Third, irrigation at the SPRF was applied without using soil moisture measurements as a correction to the checkbook, which has been previously shown to lead to over-irrigation (Laboski et al., 2001; Steele et al., 1997). Future studies investigating irrigation effects should either incorporate soil moisture measurements into soil moisture balance calculations or use more accurate irrigation scheduling methods that do not require corrections. Frequent exceedance of field capacity occurred in both irrigation treatments (Figure 1-2) because of over-irrigation resulting from failing to correct the checkbook for soil moisture measurements and from frequent precipitation events, which further limited the differences in soil moisture deficit between treatments.

Except for a brief period in June 2017, soil moisture deficit did not exceed the management allowable depletion limit. For potato with an effective rooting depth of 30 cm, soil with 4.3 cm of available water holding capacity over that depth (Hansen and Giencke, 1988), and an allowable depletion limit of 35% (Wright, 2002), the management allowable depletion limit was 1.5 cm. Exceedance of this limit was not directly factored into our irrigation scheduling procedure.

Percolation was reduced by 6% in 2016 and 10% in 2017 for the Reduced irrigation treatment compared to the Conventional treatment (Table 1-7). Differences in percolation between irrigation treatments were greatest in June 2016 and July 2017 with reductions of 28 and 38%, respectively, for the Reduced irrigation treatment compared to the Conventional treatment. These 2 mo had relatively low precipitation (Table 1-2), which resulted in few precipitation-driven percolation events. In months with relatively high precipitation, such as July 2016 and August 2017 (Table 1-2), differences in percolation between irrigation treatments were small with reductions of 7 and 5%, respectively. Therefore, Reduced irrigation is a potential strategy to decrease percolation below the root zone in humid climates, but the effectiveness is ultimately dependent on the timing and magnitude of precipitation events.

TUBER YIELD AND QUALITY

Nitrogen had a significant effect on total yield, US No. 1 yield, and the ratio of tubers greater than 170 g (Table 1-8). For total yield, the effect of N was significant for the Rate contrast. The recommended rate of 270 kg N ha^{-1} had higher total yields (72.5 Mg ha^{-1}) than the reduced rate of 180 kg N ha^{-1} (69.6 Mg ha^{-1}). Reducing the rate of N applied by a fixed amount (i.e., 33%) and without monitoring crop N status in-season had a negative impact on yield, and is consistent with recommendations that the optimal N rate for Russet Burbank potato is around 270 kg N ha^{-1} for this region (Rosen and Bierman, 2008). The interaction between Year and the Control contrast was also significant for total tuber yield. The control N treatment had a lower total yield in 2016 (51.9 Mg ha^{-1}) than in 2017 (56.7 Mg ha^{-1}), while the fertilized treatments had a similar yield in 2016 (72.2 Mg ha^{-1}) and 2017 (70.4 Mg ha^{-1}). The source of difference in yield for the control N treatment could potentially be explained by differences in soil N mineralization or nitrate leaching between years.

For US No. 1 yield, the N effect was significant for the Rate contrast (Table 1-8). Similar to the results for total yield, the recommended rate treatments had higher US No. 1 yield (51.9 Mg ha^{-1}) than the reduced rate treatments (49.8 Mg ha^{-1}), indicating that 270 kg N ha^{-1} was closer to the optimal N rate than the reduced rate. There was a significant interaction between Year and the Control contrast. The increase in US No. 1 yield for the fertilized treatments between 2016 (43.6 Mg ha^{-1}) and 2017 (58.6 Mg ha^{-1}) was greater than the increase between 2016 (31.5 Mg ha^{-1}) and 2017 (38.5 Mg ha^{-1}) for the control treatment. The control treatment in 2016 had a similar percentage of misshapen tubers (33.0%) as the fertilized treatments (35.9%), while in 2017 the control treatment had a greater percentage of misshapen tubers (29.1%) than the fertilized treatments (14.8%). A greater percentage of misshapen tubers at low N rates has been observed in previous studies (Kelling et al., 2017). However, the by Year differences in US No. 1 yield were due to an increased percentage of misshapen tubers in 2016 (35.4%) compared to 2017 (17.2%). External defects of tubers have been previously shown to occur as the result of water stress (van Loon, 1981) or variable N availability (Hopkins et al., 2008). In 2016, an exceptionally wet period occurred immediately after the first post-hilling application of UAN which delayed the second post-hilling application of UAN by around 1 wk. The combined effect of the potential for N leaching, and wet soil moisture conditions could be the source of the increase in misshapen tubers and the resulting decrease in US No. 1 yield observed in 2016. Additionally, there was a significant interaction between Year and the Source contrast. Polymer-coated urea resulted in a greater US No. 1 yield (45.1 Mg ha^{-1}) than urea (41.5 Mg ha^{-1}) in 2016, while both PCU and urea had the same yield in 2017 (58.4 Mg ha^{-1}). For the source effect in 2016, it appears that the PCU provided a more consistent supply of N than split-applied urea, which resulted in a greater US No. 1 yield. This finding is consistent with previous studies, which found that PCU maintained or increased tuber yield compared to urea applied at the same rate (Bero et al., 2014; Hyatt et al., 2010).

For tubers greater than 170 g, the N effect is significant for the Rate contrast (Table 1-8). Like the results for total and US No. 1 yield, the recommended rate treatments had a larger ratio of tubers greater than 170 g (81.6%) than the reduced rate treatments (78.7%), and there was an increase in tuber size with the addition of N fertilizer (80.6%) compared with the control treatment (62.2%). This finding is consistent with previous findings that increasing N rate has the effect of increasing tuber size (Zebarth and Rosen, 2007; Zvomuya and Rosen, 2001). The Source contrast did not have a significant effect on tuber size in this study. Other studies comparing the effect of PCU and urea sources on tuber size have had conflicting results with some studies reporting no effect (Wilson et al., 2009) and others reporting an increase in tuber size with the use of PCU (Zvomuya et al., 2003). The year effect was also significant, with 2016 having a smaller ratio of tubers greater than 170 g (72.1%) than in 2017 (82.9%). Variation in tuber size between years has also been observed previously by Sun et al. (2017) where the ratio of tubers greater than 170 g varied from 33 to 50%. Differences in tuber size between years have been attributed in previous studies to a variety of factors including stem count, tuber set, and total yield (Struik et al., 1990).

For specific gravity, the Control contrast had a significant effect on specific gravity (Table 1-8) with the fertilized treatments having a higher specific gravity (1.080) than the control treatment (1.078). The Rate contrast was also significant – the recommended rate treatments had lower specific gravity (1.079) than the reduced rate treatments (1.081). These findings are consistent with those described by Laboski and Kelling (2007), who identified a minority of studies (e.g., Zvomuya et al. (2003)) where specific gravity increased between control and fertilized treatments, but further decreased as nitrogen rate increased. Specific gravity was lower in 2016 (1.077) than in 2017 (1.082), with a significant crossing interaction for Year with the Rate contrast. A similar effect between years was observed by Wilson et al. (2009) with a decrease in specific gravity attributed to higher annual temperatures (van den Berg et al., 1990) and increased input of water (Porter et al., 1999; Yuan et al., 2003). The total water input and mean annual temperature in this study was higher in 2016 than in 2017, consistent with these previous findings.

For hollow heart incidence, there was no significant response to the main effects of year or N (Table 1-8). There was, however, a significant response to the Control contrast, with the fertilized treatments having greater incidence of internal defects (1.5%) than the control treatment (0.0%). Previous studies have found a much higher incidence of hollow heart with conflicting results on response to N fertilizer. Wilson et al. (2009) found that hollow heart had a significant response to N ranging with incidence ranging from 0.8% at 0 kg N ha^{-1} up to 10.1% for 270 kg N ha^{-1}. Zvomuya and Rosen (2001) found a nonsignificant response of hollow heart to N over the rates of 110 to 290 kg N ha^{-1} with incidence ranging from 16.0 to 21.1%.

Irrigation and its interactions did not have a significant effect on tuber yield or quality response variables (Table 1-8). For reasons previously discussed, the lack of difference in yield response was likely due to the small differences in soil moisture content between the two irrigation treatments. While even slight reductions in irrigation volume will produce a yield response in potato in arid climates (Shock et al., 1998), it is less likely that an equivalent reduction in irrigation will have a significant effect in humid climates. For example, Shae et al. (1999) examined four different methods to schedule irrigation for potato in North Dakota with annual irrigation volumes ranging from 129 to 220 mm and found no significant differences in total or US No. 1 yield. Waddell et al. (1999) applied irrigation at two rates (154 and 191 mm per year) to potato grown in Minnesota and found no significant differences in total or US No. 1 yield. However, yield reductions for potato in Minnesota under deficit irrigation have been observed under conditions when irrigation was reduced from 280 to 175 mm with the intention to observe water stress effects (Nigon, 2012).

Compared to the conventional best management practices (i.e., 270 Split and 270 CR), VR Split did not have a significant effect on any tuber yield or quality response variables (Table 1-8). Based on these results, using the NSI approach based on remote sensing measurements of MTCI and a reference plot appears to be a viable method to apply supplemental N fertilizer for potato. While an approach like the one evaluated in this study has previously been discussed as a potential strategy to optimize N fertilizer applications (Mulla, 2013; Nigon et al., 2014, 2015; Samborski et al., 2009; Zebarth and Rosen, 2007) and previously demonstrated successfully using normalized readings from chlorophyll meters with a reference plot (Denuit et al., 2002; Olivier et al., 2006), this study provides further justification that the NSI approach paired with remote sensing is an appropriate tool to manage N application in potato. The finding of the present study also supports the previous findings of van Evert et al. (2012), who evaluated supplemental N applications based on the difference between optimal N uptake and remote sensing-based estimate of N uptake using the Weighted Difference Vegetation Index for potato in The Netherlands. They found that the remote sensing-based method to apply supplemental N reduced applied N rate on average by 44 kg N ha^{-1} without reducing tuber yield.

Although these results indicate that remote sensing can be used to manage N applications in potato, several factors limit the potential for the adoption of this technology in production. One concern is that the NSI method does not produce an absolute measurement of crop N status and relies on a reference plot, which is problematic in two ways. First, establishment of a single or multiple reference plots in a production system would be logistically challenging to do. Second, because the optimal N rate may vary between years, fields, and location within a field, the NSI approach may incidentally lead to either over- or under-fertilization even with a properly established reference plot such as the one used in this study. Another concern is the limited availability of narrowband multispectral imagery analogous to CROPSCAN. For example, without narrow bands in the red, red-edge, and near-infrared spectral regions, MTCI cannot be calculated. In the absence of narrowband multispectral imagery, other vegetation indices could be calculated from readily available commercial imagery with four broad bands (red, green, blue, and near-infrared). However, camera technology is rapidly improving. New cameras recently commercially released are potentially able to overcome these limitations (e.g., RedEdge-M, MicaSense, Inc., Seattle, WA), and even hyperspectral cameras are being used more frequently.

ECONOMIC ANALYSIS

For net economic return, the Rate and Control contrasts had a significant effect (Table 1-8). The recommended rate treatments had a greater net return ($7,770 ha^{-1}) than the reduced rate treatments ($7,290 ha^{-1}). Similarly, the fertilized treatments had greater net returns ($7,600 ha^{-1}) than the control N treatment ($4,240 ha^{-1}). The cost savings of reducing N fertilizer is relatively small compared to the reduction in income related to lower total yield; therefore, applying N at rates below the optimum N rate (i.e., 180 verses 270 kg N ha^{-1}) is not economically justified for potato production. Nitrogen source did not have a significant effect on economic return, indicating that a single application of PCU and split-applications of urea and UAN are both effective N management strategies. These findings contrast with those of Zvomuya and Rosen (2001) who found that while PCU had a greater gross return than urea at the same N rate, the high cost of this fertilizer at the time ($3.75 kg N ha^{-1}) resulted in a lower net return. Wilson et al. (2009), however, found similar results to this study where PCU and urea had similar net returns. The cost of PCU at the time of their study ($1.54 kg N ha^{-1}) had decreased by more than 50% compared to Zvomuya and Rosen (2001), due to a change in supplier and improvement in manufacturing procedure, making PCU an economically viable source of N for potato.

The VR contrast in this study did not have a significant effect on net economic return (Table 1-8). Compared to 270 Split, however, VR Split had an estimated cost savings of \$20 ha^{-1} from using remote sensing instead of petiole sampling and cost savings of \$35–70 ha^{-1} from the associated reduction in N fertilizer cost. While within the scope of this small-plot study, remote sensing did not have a significant effect on net economic, these cost savings may be meaningful when remote sensing is adopted at field scales. It is important to note, however, that the estimated cost of remote sensing (\$5 ha^{-1}) is based on the cost of multispectral satellite imagery alone, and does not include the potential cost of implementing an in-field reference strip or the cost of data analysis and interpretation. VR N application using remote sensing could eventually lead to more profitable production systems at field scales, because of the ability to identify and manage for the spatial variability of crop N status found within a field. In future systems, fertigation could be applied using a VR irrigation system, where N would be applied only in the areas of the field that require supplemental fertilizer as indicated by remote sensing. Additionally, by reducing the total rate of N applied there is an unquantified environmental benefit (i.e., externality) of the remote sensing method by potentially reducing the amount of N loss to groundwater via leaching and to the atmosphere via gaseous emissions.

Reduced irrigation did not have a significant effect on net economic return (Table 1-8). There are two reasons for this. First, the marginal cost of applying irrigation in the Upper Midwest is relatively inexpensive compared to the value of tuber production. Second, there was no significant reduction in tuber yield when irrigation rate was reduced in this study. While the cost and availability of water for irrigation varies by geographic region and can be a major factor in the economics of potato production, gross returns for potato can be reduced significantly with reduction in irrigation rate (Alva, 2008). For example, Russet Burbank potato grown in eastern Oregon on silt loam soil had gross revenue decrease more than reductions in input cost as irrigation rate was reduced, resulting in lower profitability under deficit irrigation (Shock et al., 1998). Because the risk of reduced yield and gross revenue is very high for potato when irrigation is not applied at sufficient rates, there is a strong economic incentive to apply irrigation at excessive rates (Shock et al., 2007a). However, there is a long-term potential economic benefit by reducing annual irrigation rates and minimizing withdrawal from aquifers. By keeping groundwater supplies at sustainable levels, there is a greater likelihood that water will be available to irrigators under prolonged drought conditions. There are externalities associated with the economics of reducing irrigation rate. In the Upper Midwest, aquifers used for agriculture irrigation are linked to surface water resources and ecosystems, some of which are sensitive to and suffering negative impacts from groundwater depletion (Watson et al., 2014; Kraft et al., 2012).

CONCLUSIONS

Managing N using remote sensing coupled with reduced irrigation rate is a promising strategy that could be used for potato production on sandy soils in humid climates. These strategies mark another step toward optimizing N and irrigation rates to better manage the spatial and temporal variability in N and water requirements found within production fields. While the recommended rates of N and conventional rates of irrigation produced similar economic outcomes to the novel strategies evaluated in this study, these management practices have associated environmental benefits that could be achieved without a reduction in profitability. Future work to improve N and irrigation management may include (i) developing remote sensing methods that can determine absolute crop N status without the need for a reference plot (e.g., N nutrition index), (ii) developing irrigation scheduling tools that are accurate without weekly measurements of soil moisture content, and (iii) evaluating the environmental impacts of these new management practices.

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FIGURES

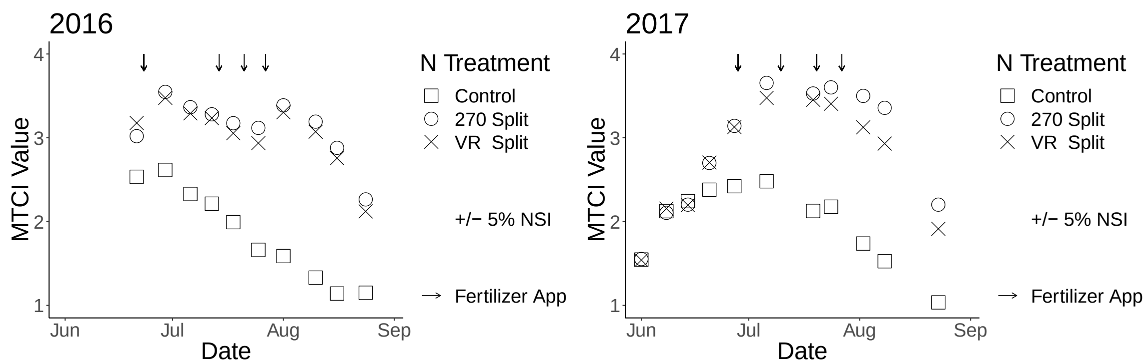

Figure 1-1. Crop N status evaluated for experimental N treatments using the MERIS Terrestrial Chlorophyll Index (MTCI) (Dash and Curran, 2004) calculated from CROPSCAN and N sufficiency index (NSI) shown separately for 2016 and 2017.

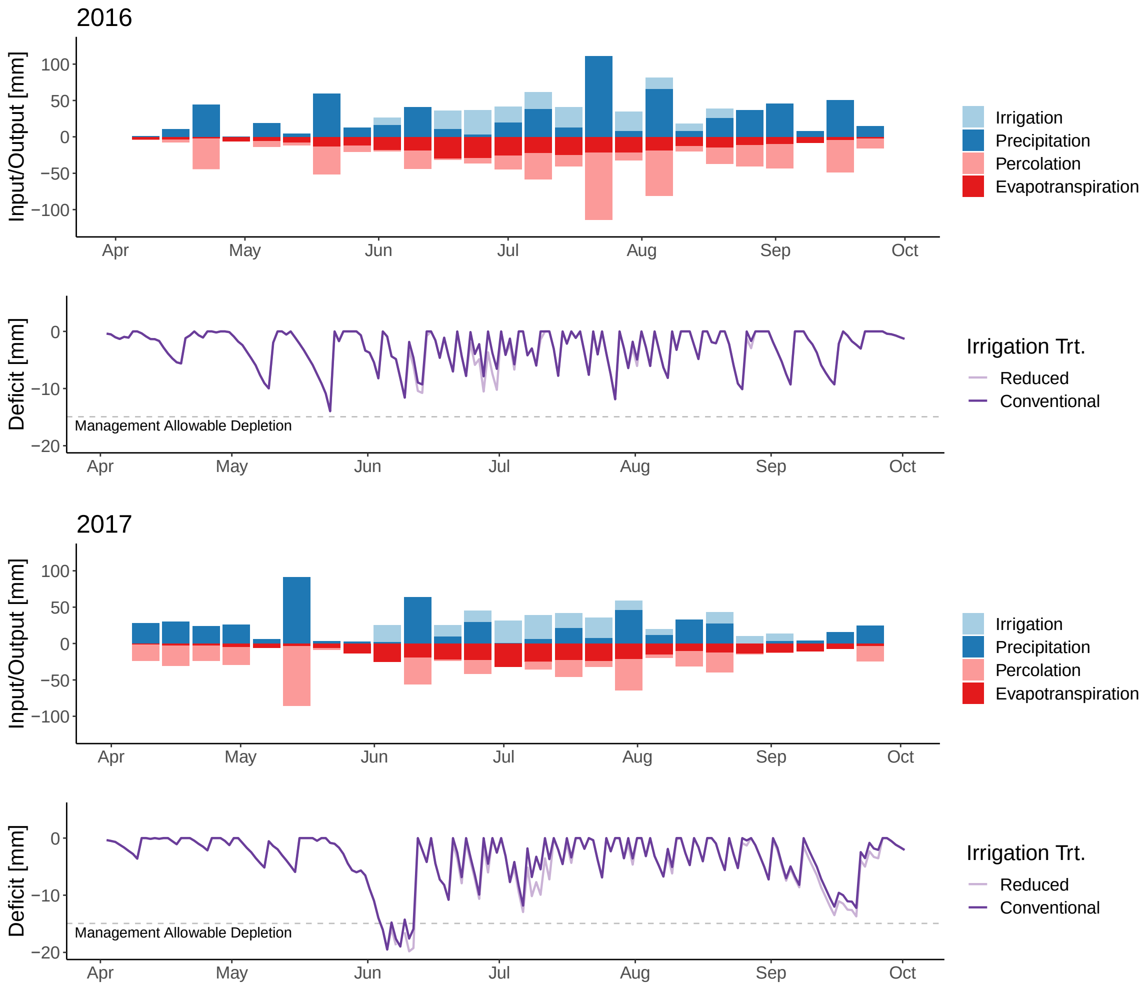

Figure 1-2. Weekly inputs of precipitation and irrigation compared against outputs of evapotranspiration and percolation shown for the Conventional irrigation treatment for 2016 and 2017, with calculated daily soil moisture deficit displayed below each year and for both irrigation treatments.

TABLES

Table 1-1. Soil chemical properties before spring planting at various depths

	0–15 cm				0–60 cm	
Year	pH†	OM‡	Bray-P1§	K¶	NO_3^-–N#	NH_4^+–N#
		%	mg kg^{-1}			
2016	5.9	1.8	34	136	2.0	1.3
2017	6.1	1.9	35	165	2.3	1.0

† pH was determined using a 1:1 soil to distilled water solution (Peters et al., 2012)

‡ Organic matter (OM) was determined with the loss on ignition method (Combs and Nathan, 1998)

§ Phosphorus concentration was determined using the Bray-P1 method (Frank et al., 1998)

¶ Potassium concentration was determined using ammonium acetate extraction (Warncke and Brown, 1998)

Nitrate and ammonium concentration was determined using conductimetric analysis (Carlson et al., 1990)

Table 1-2. Rate and timing of precipitation and experimental irrigation treatments

	2016						2017					
	May	June	July	Aug	Sept	Total	May	June	July	Aug	Sept	Total
	mm											
Precipitation†	95	72	182	145	119	613	124	106	37	119	47	433
Irrigation‡												
Reduced	–	58	69	49	–	177	–	54	104	28	–	186
Convent.	–	69	80	57	–	206	–	64	122	33	–	218

† Precipitation observed at a weather station 1 km away from the experimental site.

‡ Irrigation was applied on a fixed schedule of every 2 to 3 d using a solid-set sprinkler system at a rate determined by the checkbook method without soil moisture corrections (Steele et al., 2010; Wright, 2002) to refill the profile completely for the Conventional treatment, with the rate reduced by 15% for the Reduced treatment.

Table 1-3. Rate, source, and timing of experimental N treatments

	Planting	Emergence	Post-Emergence				Total
2016	22 Apr	1 June	23 June	14 July	21 July	27 July	
2017	29 Apr	30 May	28 June	10 July	20 July	27 July	
N Trt.	kg N ha^{-1}						
Control	45 DAP†	-	-	-	-	-	45
180 Split	45 DAP	67 Urea	17 UAN†	17 UAN	17 UAN	17 UAN	180
180 CR†	45 DAP	135 PCU†	-	-	-	-	180
270 Split	45 DAP	135 Urea	22 UAN	22 UAN	22 UAN	22 UAN	270
270 CR	45 DAP	225 PCU	-	-	-	-	270
VR Split†	45 DAP	135 Urea	*	*	*	*	180 + *

* indicates that fertilizer rate was determined in-season by remote-sensing based experimental procedures

† CR, controlled release; DAP, diammonium phosphate; UAN, urea/ammonium nitrate; PCU, polymer-coated urea; VR, variable rate.

Table 1-4. Remote sensing vegetative indices used to assess crop N stress

Index		Formula†
MERIS Terrestrial Chlorophyll Index	MTCI	$\frac{R_{751} - R_{713}}{R_{713} - R_{676}}$
Simple Ratio 8	SR8	$\frac{R_{857}}{R_{554} \text{ x } R_{704}}$
Green Ratio Vegetation Index	GRVI	$\frac{R_{NIR}}{R_G}$
Normalized Difference Vegetation Index	NDVI	$\frac{R_{NIR} - R_R}{R_{NIR} + R_R}$
Modified Soil Adjusted Vegetation Index 2	MSAVI2	$\frac{2R_{NIR} + 1 - \sqrt{(2R_{NIR} + 1)^2 - 8(R_{NIR} - R_R)}}{2}$
N Sufficiency Index	NSI	$\frac{VI}{VI_{270 \text{ Split}}}$

†$R_{\#}$ indicates narrowband percent reflectance at a given wavelength [nm]. R_G, R_R, and R_{NIR} indicate broadband percent reflectance at 520–600 nm, 660–690 nm, and 750–900 nm, respectively.

Table 1-5. Non-orthogonal contrasts used for *a priori* hypothesis testing on N treatments

	Control	180 Split	180 CR†	270 Split	270 CR	VR Split
Control	-5	+1	+1	+1	+1	+1
Rate	0	-1	-1	+1	+1	0
Source	0	-1	+1	-1	+1	0
VR†	0	0	0	-1	-1	+2

† CR, controlled release; VR, variable rate.

Table 1-6. Monitoring of in-season crop N status for the variable rate (VR) N treatment using various remote sensing, proximal sensing, and tissue sampling methods.[†]

Decision Date	2016				2017			
	23 June	14 July	21 July	27 July	28 June	10 July	20 July	27 July
Fertilizer applied to VR Split	kg N ha^{-1}							
	0	22	22	22	0	22	0	22
CROPSCAN	21 June	12 July	18 July	25 July	27 June	6 July	19 July	24 July
	NSI Value							
MTCI	0.982	**0.930**[‡]	**0.936**	0.960	0.975	**0.943**	0.976	**0.914**
SR8	0.970	**0.885**	**0.892**	**0.946**	0.971	**0.941**	0.976	**0.887**
GRVI	0.985	**0.948**	**0.946**	0.974	0.970	0.964	0.986	**0.945**
NDVI	0.999	0.997	0.996	0.998	0.992	0.999	1.001	0.996
MSAVI2	0.997	0.992	0.991	0.996	0.977	0.986	0.996	0.978
GEMS[¶]	16 June	12 July	19 July	26 July	–[¶]	2 July	16 July	29 July
	NSI Value							
GRVI	0.988	0.974	0.954	0.970	–	0.999	0.971	**0.894**
NDVI	0.995	0.988	0.989	0.990	–	1.001	0.993	0.975
MSAVI2	0.986	0.992	0.980	0.992	–	0.999	0.982	0.965
SPAD	16 June	13 July	–[§]	25 July	27 June	6 July	18 July	24 July
	NSI Value							
	1.014	0.978	–	1.018	0.992	0.960	0.965	0.959
Petiole Nitrate	16 June	13 July	–[§]	25 July	27 June	6 July	18 July	24 July
	ppm NO_3-N							
	23019	**8046**	–	**9726**	17174	**10829**	11798	**2958**

[†] GRVI, Green Ratio Vegetation Index; NDVI, Normalized Difference Vegetation Index; MSAVI2, Modified Soil Adjusted Vegetation Index 2; MTCI, MERIS terrestrial chlorophyll index; NSI, nitrogen sufficiency index; SR8, Simple Ratio 8.

[‡] Bold values indicate an identified N deficiency for a given method on a given date.

[§] Petiole nitrate and SPAD-502 were not collected between 14 July and 21 July 2016.

[¶] GEMS measurements were not collected prior to 27 June 2017.

Table 1-7. Timing and magnitude of percolation below the root zone for experimental irrigation treatments.

	2016						2017					
	May	June	July	Aug	Sept	Total	May	June	July	Aug	Sept	Total
	mm											
Percolation[†]												
Reduced	58	25	152	122	91	449	107	50	29	87	20	292
Convent.	58	35	163	131	91	479	107	57	47	91	22	324

[†] Percolation for the Reduced and Conventional irrigation treatments was estimated using a soil water balance calculation (Steele et al., 1997) with estimates of crop evapotranspiration calculated from the weather station at the SPRF (Jensen and Allen, 2016).

Table 1-8. Mean values and analysis of variance for total tuber yield, US. No 1 tuber yield, the ratio of tubers greater than 170 g, tuber specific gravity, hollow heart incidence, and net economic return.

Mean Values	Total Yield	US. No 1 Yield	Tubers > 170 g	Specific Gravity	Hollow Heart	Net Return
Year	Mg ha^{-1}	Mg ha^{-1}	%	–	%	\$ ha^{-1}
2016	68.8	41.5	72.1	1.077	1.3	6,840
2017	68.1	55.3	82.9	1.082	1.1	7,240
Irrigation						
Reduced	68.4	48.6	76.9	1.079	1.3	6,990
Convent.	68.6	48.2	78.1	1.080	1.2	7,090
Nitrogen						
Control	54.3	35.0	62.2	1.078	0.0	4,240
180 Split	69.8	48.2	77.3	1.081	1.9	7,280
180 CR†	69.4	51.5	80.0	1.080	2.3	7,310
270 Split	73.4	51.7	81.6	1.080	0.5	7,960
270 CR	71.6	52.1	81.6	1.078	1.5	7,570
VR Split†	72.3	52.1	82.3	1.080	1.3	7,870
ANOVA	Total Yield	US. No 1 Yield	Tubers > 170 g	Specific Gravity	Hollow Heart	Net Return
Year [Y]	–	**	***	***	–	–
Irrigation [I]	–	–	–	–	–	–
Nitrogen [N]	***	***	***	+	–	***
Control‡	***	***	***	*	*	***
Rate‡	**	+	**	+	–	**
Source‡	–	+	–	–	–	–
Var. Rate‡	–	–	–	–	–	–
I x N	–	–	–	–	–	–
Y x I	–	–	–	–	*	–
Y x N	*	**	–	+	–	*
Y x Control‡	**	***	+	–	–	**
Y x Rate‡	–	–	–	**	–	–
Y x Source‡	–	+	–	–	–	–
Y x Var. Rate‡	–	–	–	–	–	–
Y x I x N	–	–	–	–	–	–

***, **, *, and + denote significance at the α = 0.001, 0.01, 0.05, and 0.10 levels, respectively. – indicates a non-significant effect.

† CR, controlled release; VR, variable rate.

‡ *A priori* non-orthogonal contrast, as specified in Table 1-5

CHAPTER 2 – IMPACT OF VARIABLE RATE NITROGEN AND REDUCED IRRIGATION MANAGEMENT ON NITRATE LEACHING FOR POTATO

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Abstract

Nitrogen (N) loss from cropping systems has important environmental implications, including contamination of drinking water with nitrate. A 2-yr study evaluated the effects of six N rate, source, and timing treatments, including a variable rate (VR) N treatment based on the N sufficiency index approach using remote sensing, and two irrigation rate treatments, including conventional and reduced rate, on nitrate leaching, residual soil nitrate, and plant N uptake for potato (*Solanum tuberosum* L. cv. Russet Burbank) production in 2016 and 2017 on a Hubbard loamy sand. Nitrate leaching losses measured with suction-cup lysimeters varied between 2016 and 2017 with flow-weighted mean nitrate N concentrations of 5.6 and 12.8 mg N L^{-1}, respectively, and increased from 7.1 to 10.4 mg N L^{-1} as N rate increased from 45 to 270 kg N ha^{-1}. Despite reductions in N rate of 22 and 44 kg N ha^{-1} in 2016 and 2017, respectively, for the VR N treatment, there was no significant difference in nitrate leaching compared with the existing N best management practices (BMPs). Reducing irrigation rate by 15% decreased nitrate leaching load by 17% through a reduction in percolation. Residual soil nitrate N in the top 60 cm across all treatments (7.9 mg N kg^{-1}) suggests a risk for nitrate leaching during the nongrowing season, and plant N uptake did not explain yearly variation in nitrate leaching and residual soil nitrate. Although existing N BMPs are effective at controlling N losses, development of alternative practices is needed to further reduce the risk of groundwater contamination.

CORE IDEAS

- Improved irrigation management reduced percolation and nitrate leaching.
- Variable rate N management and existing BMPs resulted in comparable nitrate leaching.
- Elevated residual soil nitrate indicates a risk for nitrate leaching after harvest.
- Plant N uptake does not explain yearly variation in N losses.

1. INTRODUCTION

The amount of reactive nitrogen (N) entering the biosphere has increased as the result of anthropogenic sources (Galloway et al., 2004; Gruber & Galloway, 2008), and agricultural N is the largest source for anthropogenic alteration of the N cycle (Smil, 1999). Cascading effects (Galloway et al., 2003) result from this alteration, including eutrophication of freshwater and marine systems, harmful algal blooms, drinking water contamination, atmospheric N pollution, and greenhouse gas emissions (Erisman et al., 2013). Losses of reactive N to the environment have substantial social costs, estimated at US$210 billion yr^{-1} in the United States alone (Sobota, Compton, McCrackin, & Singh, 2015).

Until recently, protecting groundwater from agricultural nitrate leaching in Minnesota was pursued using voluntary measures alone (MPCA, 2013). With an increase in the incidence of private wells and public water systems with nitrate contamination exceeding the health risk limit of 10 mg N L^{-1}, new regulatory strategies have been adopted to protect groundwater degradation (MDA, 2015, 2018). These strategies require the implementation of N management best management practices (BMPs) (Rosen & Bierman, 2008) in areas with vulnerable groundwater. This regulatory policy is generally analogous to the Nitrate Directive of the European Union (Richard, Casagrande, Jeuffroy, & David, 2018; van Grinsven, Tiktak, & Rougoor, 2016; Velthof et al., 2014) and based in part on policies established to reduce nitrate leaching in Nebraska (Ferguson, 2015).

Potato (*Solanum tuberosum* L.) is grown on 94,000 ha, with a farmgate value of $857 million yr^{-1} across Minnesota, North Dakota, Wisconsin, and Michigan (USDA-NASS, 2013). Potato grown in this region has a relatively large N requirement of 270 kg

N ha^{-1} (Franzen, Robinson, & Rosen, 2018; Rosen & Bierman, 2008). Two-thirds of the potato production in this region uses supplemental irrigation (USDA-NASS, 2013) due to the sensitivity of potato to water stress (Shock, Pereira, & Eldredge, 2007) and the common practice of growing potato on sandy soils with low water-holding capacity. This cropping system has a high potential for nitrate N leaching (Shrestha, Cooperband, & MacGuidwin, 2010), and N losses measured in commercial potato fields and experimental trials have ranged from 4–257 kg N ha^{-1} with measured soil water nitrate N concentrations commonly exceeding 10 mg N L^{-1} (Zebarth & Rosen, 2007). Therefore, optimal irrigation and N management are essential to reduce nitrate N leaching losses from potato production (Alva, 2010; Meisinger & Delgado, 2002; Munoz, Mylavarapu, & Hutchinson, 2005; Quemada, Baranski, Nobel-de Lange, Vallejo, & Cooper, 2013).

Remote sensing for variable rate (VR) N management is generally regarded as one of the most important tools currently available to improve on existing in-season management practices (Mulla, 2013). Although remote sensing-based N management methods for potato have been previously suggested (Goffart, Olivier, & Frankinet, 2008; Nigon et al., 2015) and evaluated for agronomic effectiveness (Bohman, Rosen, & Mulla, 2019; van Evert et al., 2012), their effectiveness at reducing N losses has not yet been reported for potato. In a similar manner to existing in-season N management tools such as chlorophyll meters and petiole nitrate measurements (Gianquinto et al., 2004; Giletto & Echeverría, 2013; Goffart, Olivier, & Frankinet, 2011; Shrestha et al., 2010), remote sensing should be able to optimize N application by identifying occurrence of crop N stress. Additionally, remote sensing also has superior spatial and temporal resolution, expanding the potential for field-scale in-season VR N management.

Similarly, reduced volume of supplemental irrigation is a potential strategy to optimize applications in humid climates. Because excess irrigation can drive percolation below the root zone (Hergert, 1986; Martin, Gilley, & Skaggs, 1991; Quemada et al., 2013), optimizing irrigation rate and timing will minimize percolation and nitrate N leaching. Waddell, Gupta, Moncrief, Rosen, and Steele (2000) concluded that maintaining a deficit of soil water storage between irrigation events (e.g., reduced irrigation) while maintaining soil water content above the allowable depletion limit would be a beneficial practice to reduce nitrate N leaching.

A companion study was previously published detailing agronomic findings and water balance from the experiment in the present study (Bohman et al., 2019). In summary, the previous companion study found that reducing irrigation rate by 15% did not affect tuber yield in humid climates, and remote sensing was able to reduce N rate by 15% without impacting tuber yield. Additionally, the previous study found that when N rate was reduced below the recommended rate of 270 kg N ha^{-1} to 180 or 45 kg N ha^{-1}, tuber yield decreased significantly.

The primary objective of the present study was to determine the impact of N rate, source, and timing treatments, including remote sensing-based VR applications, and reduced rate of supplemental irrigation on nitrate N leaching, residual soil nitrate N, and plant N uptake.

2. MATERIALS AND METHODS

2.1. EXPERIMENTAL CONDITIONS

A plot-scale field experiment was conducted in 2016–2017 at the Sand Plain Research Farm (SPRF) in Becker, MN (45°23′ N, 93°53′ W). The soil at this station is characterized as a Hubbard loamy sand (sandy, mixed, frigid Entic Hapludolls) with a low available water-holding capacity of 0.098 cm cm^{-1} for 0- to 90-cm depth (Hansen & Giencke, 1988; USDA-NRCS, 2013). 'Russet Burbank' potato, a processing variety common to the region, was grown each year following a previous full season crop of rye (*Secale cereal* L.). Preplant soil test chemical characteristics have been reported previously, including soil organic matter in the 0- to 15-cm depth of 1.8 and 1.9% in 2016 and 2017, respectively (Bohman et al., 2019). Average air temperature and cumulative precipitation during the growing season was 19.2°C and 613 mm in 2016 and 18.5°C and 433 mm in 2017, observed at the weather station at the SPRF. Additional description of site conditions and cultural management can be found in the supplemental material or Bohman et al. (2019).

The experimental design for this study was a split plot within a randomized complete block design with four replicates. Irrigation rate and timing was the main plot treatment (with two treatments), and N rate, source, and timing was the subplot treatment (with six treatments). A plot map and detailed plot layout description is included in the supplemental materials (Supplemental Figure S1) and the companion paper (Bohman et al., 2019). Whole "B" seeds were planted on 22 Apr. 2016 and 29 Apr. 2017 with 0.3-m spacing between seeds.

Irrigation treatments included conventional irrigation rate (Conventional) based on the checkbook method (Steele et al., 2010; Wright, 2002), but without using soil moisture measurements as corrections, and reduced irrigation rate (Reduced) with the rate reduced by 15% relative to the Conventional irrigation treatment. Irrigation was applied on a fixed schedule of every 2–3 d for a total of 19 and 22 irrigation applications in 2016 and 2017, respectively, using a solid-set overhead sprinkler system. Detailed methods of irrigation application and a map showing irrigation sprinkler location (Figure 2-S1) are included in the supplemental materials. On a given date of application, irrigation was applied to the conventional plot at a rate determined by the checkbook method to refill the profile completely. The conventional treatment received 206 and 218 mm of irrigation, whereas the reduced treatment received 177 and 186 mm of irrigation in 2016 and 2017, respectively. Additional detail on the rate and timing of irrigation, including discussion of the variation in precipitation and irrigation between years, is presented in Bohman et al. (2019).

The six N treatments (Table 2-1) included a 45 kg N ha^{-1} control treatment (Control), a split-applied urea treatment at rates of 180 kg N ha^{-1} (180 Split) and 270 kg N ha^{-1} (270 Split), a controlled-release (CR) polymer-coated urea (PCU, Environmentally Smart Nitrogen [ESN], Nutrien) treatment at rates of 180 kg N ha^{-1} (180 CR) and 270 kg N ha^{-1} (270 CR), and a VR split-applied urea treatment (VR Split) based on remote sensing observations paired with the N sufficiency index (Blackmer & Schepers, 1995; Peterson, Blackmer, Francis, & Schepers, 1993). For the VR Split treatment, 270 CR was used as the well-fertilized reference. Additional detail on the implementation of the adaptive N management method used for the VR Split treatment is presented in Bohman et al. (2019).

Fertilizer at planting was diammonium phosphate applied to all N treatments as a band 2 cm below and 3 cm to each side of tubers at a rate of 45 kg N ha^{-1}. Emergence fertilizer was urea for the 180 Split, 270 Split, and VR Split and PCU for 180 CR and 270 CR. Treatments 180 Split and 270 Split received four scheduled post-hilling applications of liquid urea/ammonium nitrate (UAN) in the form of simulated fertigation using a tractor mounted sprayer immediately followed by irrigation on a 1- to 2-wk basis. Post-hilling fertilizer was applied to VR Split as UAN at a rate of 22 kg N ha^{-1} using the same simulated fertigation method as 180 Split and 270 Split when the N sufficiency index value calculated with the MERIS Terrestrial Chlorophyll Index (MTCI) (Dash & Curran, 2004) from a ground-based narrowband proximal sensor (MSR-16R, CROPSCAN) was <0.95 prior to the scheduled application date (Table 2-1).

2.2. Water sampling

Nitrate N concentration below the root zone at 1.2-m depth was monitored with suction-cup lysimeters using the methods of Venterea, Hyatt, and Rosen (2011). Suction-cup lysimeters were constructed from a 100-kPa high-flow porous ceramic suction cup (Soilmoisture Equipment Corporation) attached to a SDR-26 polyvinylchloride (PVC) pipe. One lysimeter was installed in a nonharvest row each year in each of the 48 plots immediately after planting in a vertical hole bored using an 83-mm soil auger. The suction-cup lysimeter was installed with a silica-flour slurry poured into the hole to a depth necessary to fully cover the ceramic cup. Previously removed soil was packed in around the lysimeter to refill the borehole, and a layer of powdered bentonite was applied after backfilling to prevent preferential flow. Water samples from lysimeters were collected on a weekly basis between 18 May and 6 October in 2016 and between 22 May and 6 October in 2017. There were 25 collection dates in 2016 and 18 in 2017. Nitrate concentration in the samples was determined using conductimetric procedures (Carlson, Cabrera, Paul, Quick, & Evans, 1990) with a Wescan analyzer (Wescan Instruments).

2.3. Soil and plant sampling

Vines were killed with a mechanical flail mower on 14 Sept. 2016 and 13 Sept. 2017, and tubers were mechanically harvested from a 5.5-m section of the fourth and fifth rows in the middle of the plot on 30 Sept. 2016 and 27 Sept. 2017. Samples of vine biomass were harvested by hand from a 3.0-m section of the fourth and fifth rows in the middle of the plot immediately prior to mechanical termination. Vines and tubers were weighed for fresh biomass, and a subsample was dried at 60°C and subsequently weighed for dry matter content. Dried samples were ground with a Wiley mill to pass through a 2-mm screen. Total N concentration of dried tuber and vine subsamples was determined with combustion analysis (Elementar Vario EL III, Elementar Americas) using standard methods (Horneck & Miller, 1998). Tuber and vine N uptake at harvest was determined by multiplying plant tissue dry weight by N concentration, and total plant N uptake was determined from their sum. Postharvest composite soil samples were collected on 10 Oct. 2016 and 10 Oct. 2017 from each plot at the 0- to 60-cm depth. Samples were air dried, extracted with 2 M KCl solution, and analyzed for total inorganic N (nitrate N and ammonium N) concentration using the conductimetric procedures described above. Residual soil inorganic N on a mass-per-area basis was calculated for each plot using a previously reported bulk density value of 1.60 g cm^{-3} (Hansen & Giencke, 1988).

2.4. Water balance calculations

A daily soil water balance calculation was implemented to estimate percolation below the root zone using the approach outlined by Steele, Scherer, Prunty, and Stegman (1997) and Errebhi, Rosen, Gupta, and Birong (1998). In this approach, daily percolation (D_i) was estimated to be the difference between inputs of daily precipitation (P_i) and daily irrigation (IRR_i), output of daily crop evapotranspiration (ET_i), and daily change in soil moisture storage (ΔS_i) (Equation (2-1)). In this framework, the sum of ΔS_i and the soil moisture storage on the previous day (S_{i-1}) cannot exceed field capacity [FC]. This implies that D_i is equivalent to the quantity of soil moisture in excess of FC, and that percolation of excess soil moisture occurs within a 24-h period:

$$D_i = P_i + IRR_i - ET_i - \Delta S_i, \text{ where } \Delta S_i + S_{i-1} \leq FC \qquad [2\text{-}1]$$

Observations from the weather station at the SPRF were used to quantify P_i and to estimate ET_i using the standardized reference evapotranspiration based on the Penman–Monteith approach and mean crop coefficient based on days after emergence approach detailed in Jensen and Allen (2016). Soil water balance calculations were conducted at the level of irrigation treatment with differing values of IRR_i for each treatment according to the experimental treatments, and N treatments within an irrigation treatment were assumed to have an identical soil water balance. This assumption may lead to overestimating actual evapotranspiration and underestimating percolation in the Control N treatment. However, this type of simplified water balance calculation to estimate percolation and calculate nitrate leaching load has been used in multiple previous studies for potato (Errebhi et al., 1998; Venterea et al., 2011; Wilson, Rosen, & Moncrief, 2010; Zvomuya, Rosen, Russelle, & Gupta, 2003) and for corn (*Zea mays* L.) (Andraski, Bundy, & Brye, 2000; Sexton, Moncrief, Rosen, Gupta, & Cheng, 1996; Struffert, Rubin, Fernandez, & Lamb, 2016).

2.5. NITRATE LEACHING CALCULATIONS

Cumulative nitrate N leaching load was calculated for the growing season period between 1 May and 30 September using the methods of Errebhi et al. (1998), Wilson et al. (2010), and Lord and Shepherd (1993). The measured nitrate N concentration data for each plot, linearly interpolated between sampling dates, were multiplied by the estimated volume of daily percolation resulting from the soil water balance calculation approach as previously described. Cumulative nitrate N leaching load over the growing season was then determined by summing the daily nitrate N leaching load values. Flow-weighted mean nitrate N concentration was calculated by dividing cumulative nitrate N leaching load by cumulative percolation volume over the growing season.

2.6. STATISTICAL ANALYSIS

Statistical analysis for response variables of nitrate N leaching load, flow-weighted nitrate N concentration, and residual soil nitrate N were conducted using SAS PROC GLIMMIX (SAS Institute, 2013) to test the fixed effects of study year, irrigation treatment, N treatment, and their interactions. The overall significance of each main effect, interaction effect, and of the a priori nonorthogonal contrast comparisons for N treatments (Table 2-2) were evaluated for each response variable with significance set at $P < .10$. The a priori nonorthogonal contrasts were designed to evaluate the effect of control versus fertilized N treatments (Control), the effect of 180 versus 270 kg N ha^{-1} (Rate), the effect of PCU versus split-applied urea/UAN (Source), and the effect of VR N applied using remote sensing versus conventional N BMPs (Variable Rate).

3. Results and Discussion

3.1. Nitrate leaching

Nitrate N concentrations measured with suction-cup lysimeters exhibited a general trend in both years with increasing values after emergence and N fertilizer application, and a subsequent declining trend as the season progressed (Figure 2-1). The general trend in nitrate N concentration for each year appears to be a stronger factor than that of the N treatments themselves.

Year had a significant effect on nitrate N leaching with 26 and 39 kg N ha^{-1} in 2016 and 2017, respectively (Table 2-3). Correspondingly, there were differences in both percolation and nitrate N concentration measured with suction-cup lysimeters between years (Figure 2-1). Averaged over irrigation treatments, percolation during the May to September period was calculated as 465 mm in 2016 and 308 mm in 2017. Differences in percolation between years can be attributed to greater precipitation in 2016 than in 2017 with 613 and 433 mm for each year, respectively. However, this occurred simultaneously with flow-weighted mean nitrate N concentrations in 2016 (5.6 mg N L^{-1}) that were significantly lower than those observed in 2017 (12.8 mg N L^{-1}) (Table 2-3). This type of dilution effect where observed nitrate N concentration decreases as percolation increases has been previously observed (Struffert et al., 2016). Combined, these two factors caused less nitrate N leaching in 2016 than in 2017.

Increasing percolation will generally increase nitrate N leaching load (Bowles et al., 2018). In contrast, results of our study, along with previous studies (Ochsner, Schumacher, Venterea, Feyereisen, & Baker, 2018; Venterea et al., 2011; Wilson et al., 2010), showed that increasing percolation did not correspond with increasing nitrate N leaching load due to variations in nitrate N concentration. For the present study, the differences in nitrate N concentration observed between years could be explained by greater net soil N mineralization in 2017 than in 2016, as evidenced by significantly greater tuber yield for the Control N treatment in 2017 than in 2016 (56.7 and 51.9 Mg ha^{-1}, respectively) (Bohman et al., 2019). The apparent reduction in mineralization in 2016 may be due to excessive soil moisture conditions (Dessureault-Rompré, Zebarth, Georgallas, Burton, & Grant, 2011; St. Luce, Whalen, Ziadi, & Zebarth, 2011).

Nitrate N leaching was 17% less for the Reduced irrigation treatment (30 kg N ha^{-1}) than for the Conventional irrigation treatment (36 kg N ha^{-1}) (Table 2-3). Percolation was reduced by 30 mm or 6% in 2016 and by 32 mm or 10% in 2017 with Reduced compared with Conventional irrigation during the May to September period. During June and July, the periods of the growing season when nitrate N concentrations are highest (Figure 2-1), percolation was reduced by 22 mm or 11% in 2016 and by 26 mm or 25% in 2017 with Reduced compared with Conventional irrigation. Additional results relating to the effect of irrigation and year on percolation and other components of the soil water balance, including monthly summary values and daily soil moisture content, can be found in Bohman et al. (2019). There were no significant differences in flow-weighted mean nitrate N concentration between irrigation treatments (Table 2-3), indicating that significant reductions in percolation are the primary cause of significantly reduced nitrate N leaching in the Reduced versus the Conventional irrigation treatment.

Results of this study concur with findings of previous studies evaluating the impact of irrigation management on nitrate N leaching. Waddell et al. (2000) compared conventional sprinkler irrigation to reduced-rate sprinkler irrigation as well as to drip irrigation. As the total volume of irrigation applied decreased (191, 154, and 73 mm), the volume of percolation (114, 74, and 29 mm) and nitrate N leaching load (40, 15, and 6 kg N ha^{-1}) also decreased. Saffigna, Keeney, and Tanner (1977) found that reducing irrigation applications from 435 to 245 mm, significantly decreased percolation from 465 to 275 mm and nitrate N leaching load from 208 to 128 kg N ha^{-1}.

In future studies, an improved water balance calculation should be used to reduce uncertainty of estimates from the simplified water balance calculation method used in the present study and improve the accuracy of nitrate N leaching load calculations. This could include using mechanistic soil-crop-water models or direct measurements of soil moisture content to reduce uncertainty in D_i or ΔS_i, or using remote sensing based estimates of crop evapotranspiration (Allen, Tasumi, & Trezza, 2007) to reduce uncertainty in ET_i. Adoption of these calculation methods would also improve the accuracy of irrigation scheduling tools, prevent overirrigation, and reduce percolation (Bohman et al., 2019).

Nitrate N leaching (25 kg N ha^{-1}) and flow-weighted mean nitrate N concentration (7.1 mg N L^{-1}) were significantly lower in the Control N treatment compared with the other fertilized N treatments (34 kg N ha^{-1} and 9.6 mg N L^{-1}, respectively), a 26% reduction (Table 2-3). Although this reduction in nitrate leaching is substantial, reducing N rate to

45 kg N ha^{-1} was found to reduce total tuber yield and net economic return by 24 and 44%, respectively, compared to the other fertilized N treatments (Bohman et al., 2019). The 180 N treatments had significantly less nitrate N leaching (32 kg N ha^{-1}) and lower flow-weighted mean nitrate N concentration (8.9 mg N L^{-1}) compared with the 270 N treatments (37 kg N ha^{-1}, and 10.4 mg N L^{-1}, Table 2-3). While reducing N rate from 270 to 180 kg N ha^{-1} reduced nitrate N leaching by 15%, it also reduced total tuber yield and net economic returns by 4 and 6%, respectively (Bohman et al., 2019).

There was no significant difference in nitrate N leaching load or flow-weighted mean nitrate N concentration between the VR Split and 270 N treatments, although N rate was 16% lower with the VR Split than the 270 N treatments (Table 2-3). The VR Split treatment was also found to have no significant effect on total tuber yield and net economic return compared with the 270 N treatments (Bohman et al., 2019). Future research should explore the effect of remote sensing based VR N management on nitrate leaching at field scales (Delgado, Khosla, Bausch, Westfall, & Inman, 2005).

The lack of significant difference in the N Source contrast for either nitrate N leaching load or flow-weighted mean nitrate N concentration (Table 2-3) indicates that both BMPs evaluated (i.e., CR or Split) were equally effective. Other recent studies evaluating urea with multiple split applications or PCU applied at planting or emergence have reported findings similar to the present study (Venterea et al., 2011; Wilson et al., 2010; Zvomuya et al., 2003). Historically, nitrate N leaching losses during the growing season for irrigated Russet Burbank potato grown in central Minnesota and across the Upper Midwest have been very high. Early studies on this subject observed flow-weighted mean nitrate N concentrations >40 mg N L^{-1} and nitrate N losses during the growing season of >200 kg N ha^{-1}, compared with losses of 20 kg N ha^{-1} from the control treatment (Errebhi et al., 1998; Saffigna et al., 1977). These early studies used an N fertilizer source (e.g., ammonium nitrate) and application timing (e.g., most N applied at planting) that were extremely prone to nitrate leaching losses (Shrestha et al., 2010). In contrast, the current source and timing BMPs evaluated in the present and other recent studies have reported nitrate N leaching losses of comparable magnitude to that of control treatments in the early studies, demonstrating that considerable progress has been made in reducing nitrate N leaching.

Overall, this study found that nitrate leaching was significantly reduced only for N treatments with a rate below the agronomic or economic optimum N (i.e., 270 N or VR Split treatments). Both source BMPs (i.e., CR or Split) performed equally as well by aligning soil N availability with plant N uptake and demand. Additionally, the Reduced irrigation treatment also decreased nitrate N leaching by reducing percolation driven by excessive irrigation. However, even when appropriate BMPs are used, environmental effects (e.g., precipitation, mineralization, etc.) remain the key drivers of determining the magnitude and timing of nitrate N leaching losses. These nonexperimental conditions should be considered when interpreting nitrate leaching results of this study in the context of previous potato N and irrigation management studies in the Upper Midwest (Venterea et al., 2011; Wilson et al., 2010; Zvomuya et al., 2003), and for identifying optimal BMPs across environmental conditions.

3.2. Residual soil nitrate and inorganic nitrogen

Residual soil nitrate N was measured to evaluate the potential risks of nitrate N leaching during the nongrowing season period when suction-cup lysimeter samples were not collected. There were no significant differences observed for N treatment and year on residual nitrate N, but a significant effect was observed between irrigation treatments. Conventional irrigation resulted in significantly higher residual soil nitrate N concentration in the top 60 cm than Reduced irrigation (8.6 and 7.1 mg N kg^{-1}, respectively) (Table 3). The cause of this effect is likely due to differences in mineralization. However, the reason for these differences is difficult to determine, as soil moisture status was similar between irrigation treatments at the end of the growing season (Bohman et al., 2019). A modeling approach may be needed to elucidate possible reasons for the observed effect due to irrigation. There was also a significant effect observed for the interaction between year and the Control N contrast. Residual soil nitrate was significantly lower in 2016 (6.4 mg N kg^{-1}) than in 2017 (9.3 mg N kg^{-1}) for the Control N treatment, whereas the fertilized N treatments had similar residual nitrate N in both years (8.5 and 7.2 mg N kg^{-1}). This is likely due to increased mineralization in 2017, as previously discussed. Residual inorganic N had a similar response to treatments and environmental effects as residual soil nitrate N (Table 2-3), explained by the relatively high proportion of residual inorganic N found in the nitrate N form (94 and 82% in 2016 and 2017, respectively). Averaged across treatments and years, the quantity of residual soil inorganic N (86 kg N ha^{-1}) is more than twice the nitrate leaching load (33 kg N ha^{-1}) lost during the growing season.

Overall, the levels of residual soil nitrate N observed in this study (7.1 to 8.6 mg N kg^{-1}) are higher than has been observed in previous studies on irrigated potato at this location by Errebhi et al. (1998) (0.9–1.8 mg N kg^{-1}), Zvomuya et al. (2003) (3.1–7.5 mg N kg^{-1}), Wilson et al. (2010) (1.8–3.1 mg N kg^{-1}), and Venterea et al. (2011) (1.6–2.2 mg N kg^{-1}). The present study clearly indicates that there remains a significant potential for nitrate N leaching loss during subsequent winter months in some years. These results also indicate that changes in N cycling dynamics (e.g., crop N uptake, denitrification, volatilization, mineralization, and nitrate N leaching) that result from variable environmental conditions are a major impediment to mitigating losses of N to the environment. Although the exact cause of high residual soil nitrate N in the present study is unknown, it is expected that climate change will produce greater variability in soil N cycling ultimately leading to an increased potential for N losses, which N BMPs alone will have limited ability to control (Bowles et al., 2018).

To mitigate N losses following potato production, Shrestha et al. (2010) recommends planting winter wheat (*Triticum* spp.), rye, ryegrass (*Lolium multiflorum* Lam.), or triticale (× *Triticosecale* Wttm.) cover crops immediately after harvest in the fall to reduce nitrate N leaching. These crops are winter hardy and are able to produce high biomass, resulting in uptake of residual soil N, in a short period of time. However, this approach may be ineffective in the Upper Midwest due to cold temperatures between potato harvest in the fall and soil freeze up (Bundy & Andraski, 2005). Future work should explore the effect of various cover crops and alternative crop rotations on nitrate leaching losses from potato cropping systems.

In general, strategies such as diversifying crop rotations or using cover crops, developing precision agriculture technology to predict crop N and water demand, and watershed-scale mitigation practices will also be needed to reduce residual soil N and nitrate leaching (Cherry, Shepherd, Withers, & Mooney, 2008; Robertson & Vitousek, 2009). Although these strategies can be expensive to implement and may require public investment to be made economically feasible, they cannot be ignored in future efforts to reduce the social and environmental impacts of N losses from agriculture.

3.3. Plant nitrogen uptake

Significant differences in plant N, tuber N, and vine N uptake were also observed between N treatments, but there were no significant differences observed for the effects of irrigation or for year (Table 2-3). As N rate increased from 45 to 270 kg N ha^{-1}, plant N uptake increased from 110 to 257 kg N ha^{-1}, tuber N uptake increased from 103 to 221 kg N ha^{-1}, and vine N uptake increased from 7 to 40 kg N ha^{-1}. Because tuber N and vine N uptake were not significantly different between years, the plant N uptake component of the N balance cannot explain differences in nitrate N leaching or residual soil nitrate N between years.

There was also a significant interaction effect between Year and the Variable Rate N contrast. Tuber N uptake was significantly greater in 2016 than in 2017 (218 and 187 kg N ha^{-1}, respectively) for the VR Split N treatment, whereas the 270 CR and 270 Split N treatments had similar tuber N uptake in both years (218 and 217 kg N ha^{-1}, respectively). This effect could be explained by the reduced rate of N applied to the VR Split N treatment in 2017 compared with 2016 (224 and 246 kg N ha^{-1}, respectively). Notably, the companion study found that the effect of the Variable Rate N contrast and the interaction effect between Year and the Variable Rate N contrast did not have a significant effect on tuber yield. Therefore, the reduction in plant N uptake associated with the VR Split N treatment did not reduce yield, suggesting that the VR Split N treatment resulted in increased N use efficiency. Interpreting numerical differences in plant N on an absolute basis is difficult because the optimal plant N level directly depends on the level of biomass production (Gastal, Lemaire, Durand, & Louarn, 2015; Sadras & Lemaire, 2014). Future work requires greater discussion of this topic and on N use efficiency for the treatments evaluated in this study.

4. CONCLUSIONS

Given the concurrence of this study with the findings of past studies, there is clear evidence that the existing N BMPs for potato are effective at reducing N leaching losses. Multiple split applications of urea or PCU applied at the recommended rate can significantly reduce nitrate leaching, with levels approaching those of the control treatment in some years. However, in some years, flow-weighted mean nitrate N concentration from even a low N treatment (e.g., 45 kg N ha^{-1}) can approach or exceed the health risk limit of 10 mg N L^{-1}. This indicates that environmental factors, including the timing and magnitude of precipitation and soil N mineralization, are important factors determining nitrate leaching losses. Because these environmental factors cannot be controlled for by N management practices alone, changes in other management practices, including irrigation, are necessary to reduce N losses further. The N BMPs should continue to be promoted for their effectiveness at minimizing N leaching losses; however, based on this study, it is critical to recognize that these practices by themselves will not be sufficient in all years to obtain water quality goals. Improved irrigation management has the potential to further reduce nitrate leaching losses beyond what is possible with N BMPs alone. By optimizing the timing and rate of irrigation applications, percolation can be reduced which in turn will reduce nitrate leaching. Future research, particularly in humid climates, should continue to explore the effects of improved irrigation management strategies on nitrate leaching.

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FIGURES

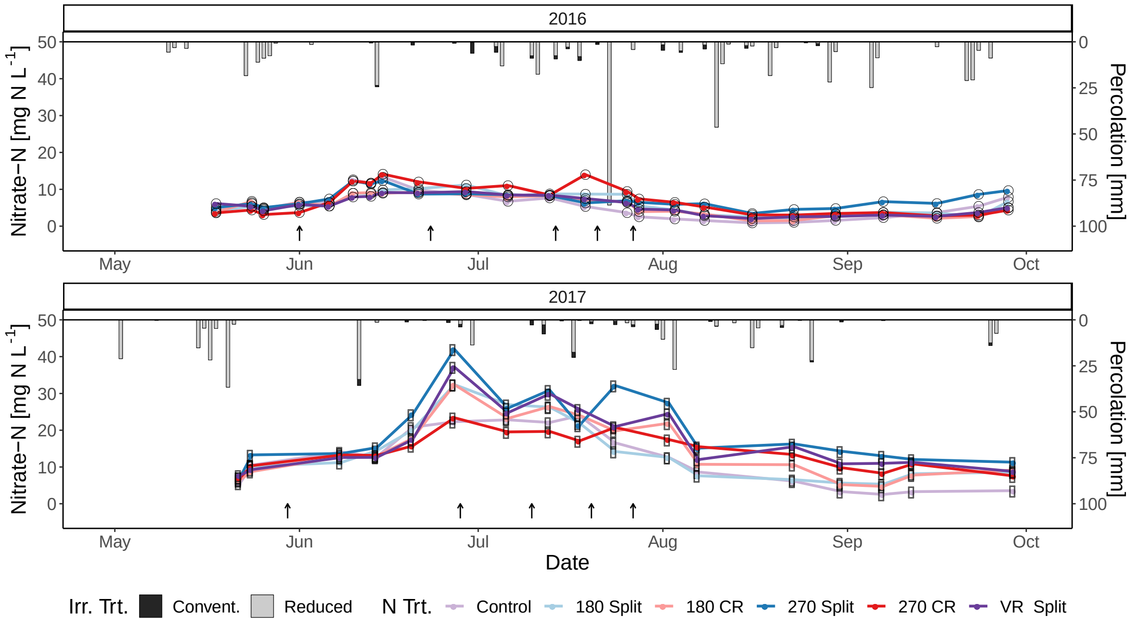

Figure 2-1. Mean nitrate N concentration values for potato production averaged over N treatment (N Trt.) and calculated daily percolation values, for each irrigation treatment (Irr. Trt.), shown for each year. Daily percolation values for each treatment are plotted in an overlapping manner. On dates where the Conventional bar (black) extends beyond the Reduced bar (gray), this indicates the daily quantity of percolation for Conventional was greater than that for Reduced. The visible portion of the bar for the Conventional irrigation treatment represents the amount of daily percolation that is over and above that of the Reduced irrigation treatment. Timing of emergence and postemergence N fertilizer applications is indicated with arrows. Percolation is shown as the vertical bars descending from the *y* axis. Nitrate N concentration is shown with colored points to the indicated mean value for each N treatment, and colored lines indicating linear interpolation between suction-cup lysimeter measurement dates. CR, controlled release; VR, variable rate.

TABLES

Table 2-1. Rate, source, and timing of experimental N treatments

Treatment [a]	Planting	Emergence	Post-Emergence				Total
	22 Apr 2016 & 29 Apr. 2017	1 June 2016 & 30 May 2017	23 June 2016 & 28 June 2017	14 July 2016 & 10 July 2017	21 July 2016 & 20 July 2017	27 July 2016 & 27 July 2017	
	kg N ha^{-1}						
Control	45 DAP [b]	–	–	–	–	–	45
180 Split	45 DAP	67 urea	17 UAN [c]	17 UAN	17 UAN	17 UAN	180
180 CR	45 DAP	135 PCU [d]	–	–	–	–	180
270 Split	45 DAP	135 urea	22 UAN	22 UAN	22 UAN	22 UAN	270
270 CR	45 DAP	225 PCU	–	–	–	–	270
VR Split (2016)	45 DAP	135 urea	–	22 UAN	22 UAN	22 UAN	246
VR Split (2017)	45 DAP	135 urea	–	22 UAN	–	22 UAN	224

[a] CR, controlled release; VR, variable rate.

[b] DAP, diammonium phosphate.

[c] UAN, urea/ammonium nitrate.

[d] PCU, polymer-coated urea.

Table 2-2. Nonorthogonal contrasts used for a priori hypothesis testing on N treatments

	Control	180 Split	180 CR [a]	270 Split	270 CR	VR Split
Control	-5	+1	+1	+1	+1	+1
Rate	0	-1	-1	+1	+1	0
Source	0	-1	+1	-1	+1	0
VR [b]	0	0	0	-1	-1	2

[a] CR, controlled release.

[b] VR, variable rate.

Table 2-3. Mean values and ANOVA for growing season nitrate N leaching load, growing season flow-weighted nitrate N concentration, residual soil nitrate concentration (0–60 cm), residual soil inorganic N (nitrate N and ammonium N) content (0–60 cm), and plant N uptake, composed of tuber N uptake and vine N uptake, measured at harvest.

Source of Variation	Nitrate Load	Nitrate Conc.	Residual Nitrate	Residual Inorg. N	Plant N Uptake	Tuber N Uptake	Vine N Uptake
	kg N ha^{-1}	mg N L^{-1}	mg N kg^{-1}	kg N ha^{-1}	kg N ha^{-1}	kg N ha^{-1}	kg N ha^{-1}
Mean value							
Year							
2016	26	5.6	8.2	83	209	185	24
2017	39	12.8	7.5	88	212	182	29
Irrigation							
Reduced	30	8.7	7.1	80	212	185	27
Convent.	36	9.6	8.6	91	209	183	26
Nitrogen [a]							
Control	25	7.1	7.9	85	110	103	7
180 Split	32	8.9	7.4	79	204	183	21
180 CR	31	8.8	8.4	90	202	180	22
270 Split	40	11.2	8.2	91	260	221	40
270 CR	35	9.6	7.7	83	253	215	38
VR Split	33	9.4	7.4	86	234	203	31
ANOVA							
Year [Y]	** [b]	***	–	–	–	–	–
Irrigation [I]	+	–	+	+	–	–	–
Nitrogen [N]	–	+	–	–	***	***	***
Control [c]	*	*	–	–	***	***	***
Rate	+	+	–	–	***	***	***
Source	–	–	–	–	–	–	–
Var. Rate	–	–	–	–	***	***	*
I x N	–	–	–	–	–	–	–
Y x I	–	–	–	–	–	–	–
Y x N	–	–	*	*	*	**	–
Y x Control	–	–	**	*	–	+	–
Y x Rate	–	–	–	–	–	–	–
Y x Source	–	–	–	–	–	–	+
Y x Var. Rate	–	–	–	–	+	***	–
Y x I x N	–	–	–	–	–	–	–

[a] CR, controlled release; VR, variable rate.

[b] + indicates significance at the α = .10 level; − indicates a nonsignificant effect.

[c] A priori nonorthogonal contrast, as specified in Table 2-2.

*, **, *** Significant at the .05, .01, and .001 probability levels, respectively.

SUPPLEMENTAL MATERIALS

MATERIALS AND METHODS – EXPERIMENTAL CONDITIONS

Apart from experimental N and irrigation treatments, all management and cultural practices were managed by the staff at the SPRF in accordance with common practices for the region (Egel, 2017) and other macro-nutrients were applied based on University of Minnesota soil test recommendations (Rosen, 2018). A weather station (Campbell Scientific, Logan, UT) located at the SPRF and 1 km away from experimental plots recorded precipitation, maximum and minimum temperature, solar radiation, relative humidity, and wind speed every hour.

Each replicate was separated by a 15.2 m buffer of rye and irrigation blocks within replicates were separated by a 9.1 m buffer alley (Figure 2-S1). Experimental plots were 6.4 m wide (seven rows of 0.9 m width) and 6.1 m long with an additional 1.5 m buffer for plots located at the edge of the irrigation block. A 3.1 m buffer separated sub-plots within main plots that were colocated in the same set of seven rows. The field used in this study has an extensive history of annual cropping including potato in the rotation.

Impact sprinkler heads (RainBird 30H, Azusa, CA) were placed on risers at a height of 1 m and spaced at a distance of 7.6 m with lateral lines located along the edge of main plots (Figure 2-S1). Sprinkler nozzles diameters of 3.57 and 3.97 mm were used in the main plots assigned to Reduced and Conventional irrigation treatments, respectively. Irrigation application rate on average was 7.6 mm hr-1, and the typical irrigation application depth was 7.6 mm. An irrigation uniformity test was conducted on 15 August 2016 and 24 August 2017, and found that irrigation was applied to the Reduced treatment at a rate of 83 and

87% relative to the Conventional treatment, respectively, with a coefficient of variation on each date and pooled across treatments of 21 and 31%, respectively. Runoff from irrigation applications were not observed, with the exception of leaks from the lateral irrigation pipe itself.

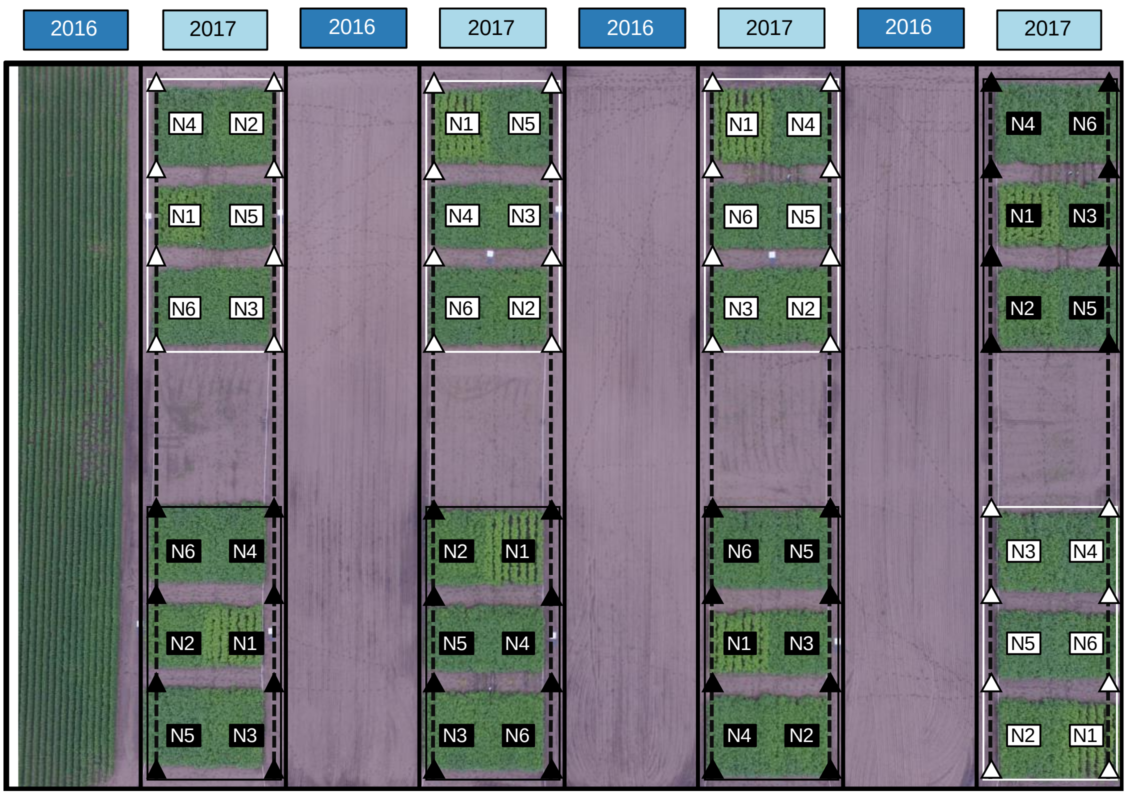

Figure 2-S1. Plot map identifying key characteristics of experimental design and treatment design used in this study overlaid on aerial imagery collected on 19 July 2017. Randomized complete block design replicates are identified by study year. Main plot locations are identified using rectangles with Reduced irrigation treatment locations shown in white and Conventional irrigation treatment locations shown in black. Solid set irrigation pipe locations are indicated with dashed black line, and irrigation sprinkler head location indicated with triangles with sprinkler heads used for Reduced irrigation treatment in white and for Conventional irrigation treatment in black. Subplots locations are labeled with N treatments where N1 represents Control N, N2 represents 180 Split, N3 represents 180 CR, N4 represents 270 Split, N5 represents 270 CR, N6 represents VR Split.

CHAPTER 3 – RELATING NITROGEN USE EFFICIENCY TO NITROGEN NUTRITION INDEX FOR EVALUATION OF AGRONOMIC AND ENVIRONMENTAL OUTCOMES IN POTATO

This chapter has been published in Field Crops Research:

Bohman, B.J., C.J. Rosen, and D.J. Mulla. (2021). Relating Nitrogen Use Efficiency to Nitrogen Nutrition Index for Evaluation of Agronomic and Environmental Outcomes in Potato. Field Crops Res., 262. doi.org/10.1016/j.fcr.2020.108041.

ABSTRACT

Maximizing nitrogen (N) use efficiency [NUE] is commonly identified as a key strategy to improve both agronomic and environmental outcomes; however, interpretation of NUE requires explicit consideration of crop N status. In this study, we derived a set of novel theoretical relationships between the nitrogen nutrition index [NNI] and NUE used to better interpret values for nitrogen uptake efficiency [NUpE] and nitrogen utilization efficiency [NUtE]. A small-plot trial for potato [*Solanum tuberosum* (L.) 'Russet Burbank'] was conducted in 2016 and 2017 in Central Minnesota, USA, on a Hubbard loamy sand with six N rate, source, and timing treatments and two irrigation rate treatments. Impacts of treatments on NNI, NUpE, NUtE, NUE, biomass, harvest index, and potential N losses were interpreted within the context of a theoretical quantitative relationship between NUE and NNI. We found that for a constant NNI value, NUtE values increased non-linearly as biomass increased; at an NNI value of 1.0, this relationship defines the critical N utilization efficiency curve. As N rate increased from 40 to 270 kg N ha^{-1}, NUtE significantly decreased from 109.8–69.7 g g^{-1} N, corresponding with a significant increase in both biomass (from 12.0–17.8 Mg ha^{-1}) and in NNI (from 0.520 to 0.973), respectively. Additionally, we found that potential N losses (e.g., leaching) decreased as NUpE increased, or as total N inputs decreased. Potential N loss was lower in 2016 than 2017 (135 and 187 kg N ha^{-1}, respectively) due to both greater NUpE and lower total N input from all sources in 2016 (0.602 g N g^{-1} N and 339 kg N ha^{-1}, respectively) than in 2017 (0.526 g N g^{-1} N and 395 kg N ha^{-1}, respectively). Interpreting NUE to evaluate agronomic and environmental outcomes requires separate consideration of its constituent factors (e.g., NUpE, NUtE, and HI) and explicit consideration of both NNI and biomass.

HIGHLIGHTS

- Nitrogen use efficiency [NUE] is best understood in terms of its constituent parts.
- Interpreting N utilization efficiency depends on both N nutrition index and biomass.
- A critical N utilization efficiency curve can be defined based on previous theory.
- Increasing N uptake efficiency [NUpE] will reduce N losses to the environment.
- Maximizing NUE does not necessarily improve agronomic or environmental outcomes.

1. INTRODUCTION

In terms of food and economic value, potato is respectively the third and fifth most important global crop (Haverkort and Struik, 2015; Devaux et al., 2014). While most potato production has historically taken place in the developed world, cultivation is now expanding in areas of the developing world including East Africa, and South and East Asia (Haverkort and Struik, 2015; Stokstad, 2019). Therefore, improving potato production is important to sustain global food security (Devaux et al., 2014). Sufficient water, supplied either from precipitation or irrigation, and N, supplied either from mineralization or application of N fertilizer, is necessary to maximize yield (Shock et al., 2007a; Zebarth and Rosen, 2007). Potato is especially sensitive to water and N stress due in part to having a shallow root system (Lesczynski, 1976). Poor management of N or irrigation inputs in potato has also been linked with negative environmental impacts, such as nitrate leaching to groundwater or gaseous emission of nitrous oxide (Shock et al., 2007b; Vos, 2009).

When viewed within an agronomic framework, the key solution to the reducing the reactive nitrogen (N) cascade (Galloway et al., 2003) is improvement of N use efficiency [NUE] (Lassaletta et al., 2014; Raun and Schepers, 2008), which represents crop yield or biomass produced per unit N supplied (Bock, 1984). This approach is analogous to the 4R best management practice [BMP] framework and focuses on using the right source of fertilizer applied at the right rate and right time, and in the right place (Bruulsema et al., 2009). These BMPs are widely recommended and utilized with the goal of improving NUE (Davidson et al., 2015; Meisinger et al., 2008), and mitigating the largest source of N losses from agricultural systems – mismatched timing of N availability with crop N demand (Robertson and Vitousek, 2009).

However, the 4R approach has limited potential to improve NUE and reduce N losses (Stewart and Lal, 2017). Primarily, this is the result of variability in the optimal rate of N fertilizer (e.g., economic optimum N rate) between growing seasons, which often leads to over application of N (Nigon et al., 2019). Additionally, despite effectiveness at reducing N losses, some 4R BMPs can be prohibitively expensive to adopt (Zhang et al., 2015). Improvements in NUE are also limited by fundamental factors beyond cultural and management practices such as crop genetics, climate conditions, and soil characteristics (Baligar et al., 2007; Fageria et al., 2008). While 4R BMPs are generally regarded as an important tool to improve NUE, they are insufficient alone to reduce losses of reactive N from agricultural systems to meet water quality or other environmental goals (Christianson et al., 2018; Lazarus et al., 2014).

Many definitions of NUE and other related metrics exist (Fageria et al., 2008; Tiwari et al., 2018). However, one commonly adopted framework defines NUE as the product of N uptake efficiency [NUpE], the efficiency of crop uptake of available N, and N utilization efficiency [NUtE], the efficiency of yield production based on N uptake (Bock, 1984). Variants within this framework include basing calculations of NUpE on N fertilizer applied only rather than accounting for all N sources such as soil N mineralization (Errebhi et al., 1999), while other studies on NUpE accounted for mineralization by using the relative difference in N uptake between a control treatment and a fertilized treatment (Errebhi et al., 1998b; Zvomuya et al., 2002). For NUtE, some previous studies have based their calculation on total plant biomass instead of yield (Swain et al., 2014; Zebarth et al., 2004). Without accounting for all sources of N, NUpE based on N fertilizer alone fails to capture the true characteristics of the soil-crop N cycle (Gastal et al., 2015; Zebarth et al., 2004).

While yield is the agronomic outcome of greatest economic significance, the partitioning of biomass into the yield fraction is a key process that operates by separate physiological mechanisms other than biomass production. Harvest index [HI], the ratio of yield to total crop biomass, is an important characteristic to consider explicitly and separately from the other components in the calculation of NUE because HI can have a complex response to N, other management and environmental factors, and can vary by genotype (Gastal et al., 2015; Giller et al., 2004; Hawkesford, 2012; Lammerts van Bueren and Struik, 2017; Ospina et al., 2004; Raun and Johnson, 1999; Tiwari et al., 2018).

In order to improve agronomic and environmental outcomes, the maximization of NUE and of all its related components is commonly defined as a key objective of management practices and breeding programs (Baligar et al., 2007; Raun and Schepers, 2008). However, the conceptual basis for maximization of NUE as the appropriate objective function to achieve these goals does not have a strong basis in theory.

The N nutrition index [NNI] is a diagnostic tool used to quantify crop N status based upon theoretical understanding of the allometric relationship between crop biomass and N concentration necessary to maximize growth (Lemaire et al., 2008). Previous work by Lemaire et al. (1996), Gastal et al. (2015), and Sadras and Lemaire (2014) has indicated that accounting for crop N status using the NNI approach is necessary to interpret the relationship between NUE and agronomic or environmental outcomes. As crop biomass increases, the marginal quantity of N necessary to maximize relative growth rate decreases (Sadras and Lemaire, 2014; Gastal et al., 2015). Agronomic response to N can also be interpreted using the NNI framework which is more generalizable than an interpretation in terms of rates, source, or timing of N applied (i.e., 4Rs) (Gastal et al., 2015; Lemaire and

Meynard, 1997; Sadras and Lemaire, 2014). Biomass and N uptake measured immediately prior to harvest can be used to determine NNI and evaluate the relative performance of various N management practices (Chambenoit et al., 2004; Caviglia et al., 2014). In this manner, end-of-season NNI serves as an agronomic performance metric for N management and an indicator of over-application of N and potential for environmental losses (Herrmann and Taube, 2005). Additionally, previous studies have identified the connection between increasing NUE and reducing N losses to the environment (Alva et al., 2006; Delgado, 2002). This includes a demonstrated co-regulating relationship between both crop N status (i.e., NNI) and soil nitrate concentration on the rate of N uptake (Devienne-Barret et al., 2000; Sadras and Lemaire, 2014), indicating that for any level of soil nitrate concentration, maximizing crop N uptake and reducing N susceptible to environmental loss requires conditions of sufficient crop N status.

Understanding the tradeoffs between maximizing agronomic production and the resulting potential for loss of N to the environment is critical to interpreting values of NUE. While true "optimal" management solutions are not possible to obtain under real-world conditions, understanding the relationship between the factors that lead to constraints is essential to improve desired outcomes (Sadras and Dennison, 2016). However, a theoretical quantitative relationship between NUE and the NNI theoretical framework has not been previously conceptualized. Therefore, the relationships between NNI, NUE, and potential N losses should be further defined in order to describe their relationship with agronomic and environmental outcomes.

This study is a companion paper to two previously published papers in which we presented agronomic findings for tuber yield and quality (Bohman et al., 2019), and environmental impacts from nitrate leaching and residual soil N (Bohman et al., 2020). This research was based on a two-year study evaluating N rate, source, and timing treatments, including remote sensing based variable rate applications, and reducing rate of supplemental irrigation compared to conventional management practices for potato grown on a sandy soil in a humid climate. In summary, the agronomic companion paper found that reducing irrigation rate by 15 % did not impact tuber yield in humid climates, and remote sensing was able to reduce N fertilizer rate by 15 % without impacting tuber yield. The environmental impact companion paper demonstrated that reduced irrigation decreased nitrate leaching by 17 % through a reduction in percolation, while flow-weighted mean nitrate concentration increased from 7.1–10.4 mg N L^{-1} as N rate increased from 45 to 270 kg N ha^{-1}, and residual soil nitrate was not affected by either N or irrigation treatment.

The primary objectives of this study were to (1) derive a theoretical quantitative relationship between the N nutrition index and N use efficiency directly following from the above-mentioned theoretical work, (2) identify relationships between N uptake efficiency and N utilization efficiency with environmental and agronomic objectives, respectively, and (3) evaluate the effect of experimental N and irrigation treatments within the context of this novel quantitative framework.

2. Materials and methods

2.1. Experimental design

A plot-scale field experiment was conducted in 2016−17 at the Sand Plain Research Farm [SPRF] in Becker, MN (45° 23′ N, 93° 53′ W). Mean air temperature at this station is 7.1

°C and mean annual precipitation is 809 mm (Arguez et al., 2010). The soil at this station is characterized as a Hubbard loamy sand (Sandy, mixed, frigid Entic Hapludolls) and excessively well drained with low available water holding capacity of 0.098 cm cm^{-1} for 0−90 cm depth (Hansen and Giencke, 1988; USDA NRCS, 2013). Russet Burbank potato, a processing variety common to the region, was grown each year following a previous full season crop of rye [*Secale cereal* (L.)]. Pre-plant soil test chemical characteristics have been reported previously, including soil organic matter in the 0−15 cm depth of 1.8 and 1.9 % and soil pH of 5.9 and 6.1 in 2016 and 2017, respectively (Bohman et al., 2019). Apart from experimental N and irrigation treatments, all management and cultural practices were managed by the staff at the SPRF in accordance with common practices for the region (Egel, 2017) and other macro-nutrients were applied based on University of Minnesota soil test recommendations (Rosen, 2018). A weather station (Campbell Scientific, Logan, UT) located at the SPRF and 1 km away from experimental plots recorded precipitation, maximum and minimum temperature, solar radiation, relative humidity, and wind speed every hour. Average observed air temperature during the growing season in 2016 and 2017 was 19.2 and 18.5 °C. Cumulative observed precipitation during the growing season in 2016 and 2017 was 613 and 433 mm.

The experimental design for this study was a split-plot within a randomized complete block design with four replicates. Irrigation rate and timing was the main plot treatment (with two treatments) and N rate, source, and timing was the sub-plot treatment (with six treatments). Each replicate was separated by a 15.2 m buffer of rye and irrigation blocks within replicates were separated by a 9.1 m buffer alley. Experimental plots were 6.4 m wide (seven rows of 0.9 m width) and 6.1 m long with an additional 1.5 m buffer for plots located at the edge of the irrigation block. A 3.1 m buffer separated sub-plots within main plots that were co-located in the same set of seven rows. Whole “B” seeds were planted on 22 April 2016 and 29 April 2017 with 0.3 m spacing between seeds. Vines were killed with a mechanical flail mower on 14 Sept. 2016 and 13 Sept. 2017 and tubers were mechanically harvested from a 5.5-m section of the fourth and fifth rows on 30 Sept. 2016 and 27 Sept. 2017. Samples of vine biomass were harvested by hand from a 3.0 m section of the fourth and fifth rows immediately prior to mechanical termination.

Irrigation treatments included conventional irrigation rate (Conventional) based on the Checkbook method (Steele et al., 2010; Wright, 2002) but without using soil moisture measurements as corrections, and reduced irrigation rate (Reduced) with the rate reduced by 15 % relative to Conventional. Irrigation was applied on a fixed schedule of every 2–3 days for a total of 19 and 22 irrigation applications in 2016 and 2017, respectively, using a solid-set overhead sprinkler system. On a given date of application, irrigation was applied to the Conventional plot at a rate determined by the Checkbook method to refill the profile completely. The Conventional treatment received 206 and 218 mm of irrigation, while the Reduced treatment received 177 and 186 mm of irrigation in 2016 and 2017, respectively. Additional detail on the rate, timing, and method of irrigation is presented in Bohman et al. (2019) and Bohman et al. (2020).

The six N treatments (Table 3-1) included a 45 kg N ha^{-1} control treatment (Control), a split-applied urea treatment at rates of 180 kg N ha^{-1} (180 Split) and 270 kg N ha^{-1} (270 Split), a controlled release [CR] polymer coated urea [PCU; Environmentally Smart Nitrogen [ESN] (Nutrien Inc., Saskatoon, SK)] treatment at rates of 180 kg N ha^{-1} (180 CR) and 270 kg N ha^{-1} (270 CR), and a variable rate [VR] split-applied urea treatment (VR

Split) based on remote sensing observations paired with the N sufficiency index [NSI] (Blackmer and Schepers, 1995; Peterson et al., 1993). For the VR Split treatment, 270 CR was used as the well-fertilized reference. Additional detail on the implementation of the adaptive N management method used for the VR Split treatment is presented in Bohman et al. (2019). Fertilizer at planting was diammonium phosphate [DAP] applied as a band 2 cm below and 3 cm to each side of tubers to all N-treatments at a rate of 45 kg N ha^{-1}. Emergence fertilizer was urea for the 180 Split, 270 Split, and VR Split and PCU for 180 CR and 270 CR. Treatments 180 Split and 270 Split received four scheduled post-hilling applications of liquid urea/ammonium nitrate [UAN] in the form of simulated fertigation using a tractor mounted sprayer immediately followed by irrigation on a 1- to 2-week basis. Post-hilling fertilizer was applied to VR Split as UAN at a rate of 22 kg N ha^{-1} using the same simulated fertigation method as 180 Split and 270 Split when the NSI value calculated with the MERIS Terrestrial Chlorophyll Index [MTCI] (Dash and Curran, 2004) from a ground-based narrowband proximal sensor (MSR-16R, CROPSCAN, Inc., Rochester, MN) was less than 0.95 prior to the scheduled application date (Table 3-1).

2.2. NITROGEN BALANCE

A partial N mass balance for each experimental treatment was calculated using the methods of Errebhi et al. (1998a). This approach accounted for inputs [N_{Input}] comprising measured initial soil inorganic N [$N_{Initial\ Soil}$], N in seed tubers [N_{Seed}], fertilizer N applied [$N_{Fertilizer}$], N supplied by irrigation [$N_{Irrigation}$] and precipitation [$N_{Precipitation}$], and estimated net soil N mineralization [$N_{Mineralization}$] (Eq. [3-1]). N outputs [N_{Output}] comprised measured residual soil inorganic N [$N_{Residual\ Soil}$], measured plant N uptake [N_{Plant}], and calculated N leaching [$N_{Leaching}$] (Eq. [3-2]). The Bohman et al. (2019) companion paper reported values of $N_{Initial}$

$_{Soil}$, and the Bohman et al. (2020) companion paper reported values of N_{Plant}, $N_{Leaching}$, and $N_{Residual\ Soil}$. In summary, initial soil N was measured using composite samples from each replicate block over 0−60 cm depth in early-April prior to establishment of experiment, and residual soil N was measured using composite samples from each plot over 0−60 cm depth in mid-October following tuber harvest – this depth is the extent of the rooting zone for potato. Soil samples were air dried, extracted with 2 M KCl solution, and inorganic N concentration (ammonium and nitrate) was determined using conductimetric procedures (Carlson et al., 1990) with a Wescan Analyzer (Wescan Instruments, Santa Clara, CA). Vines and tubers samples collected at harvest were weighed for fresh biomass and a subsample was dried at 60 °C and subsequently weighed to determine dry matter content. Total dry wt. plant biomass [W] was determined as the sum of tuber and vine dry wt. biomass. Total N concentration of dried vine and tuber subsamples was determined with combustion analysis (Elementar Vario EL III, Elementar Americas Inc., Mt. Laurel, NJ) using standard methods (Horneck and Miller, 1998). Soil water samples were collected at 1.2 m depth from each plot using suction-cup lysimeters using the methods of Venterea et al. (2011) and analyzed for nitrate concentration using the conductimetric procedure previously described. Nitrate leaching load was calculated by multiplying nitrate concentration by estimated percolation (Errebhi et al., 1998a), which was determined using a simplified water balance calculation (Steele et al., 2010; Venterea et al., 2011). Nitrate-N concentrations measured in irrigation water were 11.1 and 6.7 mg N L^{-1} and in 2016 and 2017, respectively, while precipitation had nitrate-N concentrations of less than 2 mg N L^{-1} in both years. Precipitation N was 8 and 7 kg N ha^{-1} in 2016 and 2017, respectively. Irrigation N was 19 and 12 kg N ha^{-1} in 2016 and 2017, respectively, for the Reduced treatment, and 23 and 15 kg N ha^{-1} in 2016 and 2017, respectively, for the Conventional treatment. Net soil N mineralization was estimated for each year based on the mass balance calculation for the Control N treatment, with the residual difference between all measured or calculated N_{Input} and N_{Output} assumed to be equal to $N_{Mineralization}$. The estimated value of $N_{Mineralization}$ was then assumed to be constant across all experimental units. The difference between N_{Output} and N_{Input} was then used for the fertilized N treatments to quantify N that was unaccounted for by any other component of the N balance or due to spatial variability [$N_{Unaccounted}$] (Eq. [3-3]).

$$N_{Input} = N_{Initial\ Soil} + N_{Seed} + N_{Fertilizer} + N_{Irrigation} + N_{Precipitation} + N_{Mineralization} \qquad [3\text{-}1]$$

$$N_{Output} = N_{Residual\ Soil} + N_{Plant} + N_{Leaching} \qquad [3\text{-}2]$$

$$N_{Unaccounted} = N_{Output} - N_{Input} \qquad [3\text{-}3]$$

2.3. NITROGEN USE EFFICIENCY

Nitrogen use efficiency [NUE] (g g^{-1} N), the ratio of dry wt. tuber yield [Y] (Mg ha^{-1}) to N_{Input} (kg N ha^{-1}) (Eq. [3-4]), N uptake efficiency [NUpE] (g N g^{-1} N), the ratio of N_{Plant} (kg N ha^{-1}) to N_{Input} (kg N ha^{-1}) (Eq. [3-5]), N utilization efficiency [NUtE] (g g^{-1} N), the ratio of W (Mg ha^{-1}) to N_{Plant} (kg N ha^{-1}) (Eq. [3-6]), and harvest index [HI] (g g^{-1}), the ratio of Y (Mg ha^{-1}) to W (Mg ha^{-1}), were calculated using the method of Zebarth et al. (2004). The product of NUpE, NUtE, and HI, by definition, is equivalent to NUE (Eq. [3-4]).

$$NUE = Y/N_{Input} = NUpE \cdot NUtE \cdot HI \qquad [3\text{-}4]$$

$$NUpE = N_{Plant}/N_{Input} \qquad [3\text{-}5]$$

$$\mathrm{NUtE} = W/N_{\mathrm{Plant}} \quad [3\text{-}6]$$

$$\mathrm{HI} = Y/W \quad [3\text{-}7]$$

2.4. POTENTIAL NITROGEN LOSS

It is possible to quantify the potential for N losses [$N_{\mathrm{Loss\ Potential}}$] or "leakiness" using the N mass balance approach (Eq. [3-8]). Potential pathways for loss include nitrate leaching, residual soil inorganic N which is susceptible to loss after the growing season, and denitrification or volatilization which are unaccounted for in the N mass balance. Essentially, potential N loss is equivalent to the sum of all N outputs minus plant N uptake; therefore, it is possible to relate NUpE to $N_{\mathrm{Loss\ Potential}}$ (Eq. [3-9]). For a given level of N_{Input}, increasing NUpE will increase the fraction of N_{Input} utilized by the plant and therefore decrease the fraction of N_{Input} susceptible to loss.

$$N_{\mathrm{Loss\ potential}} = N_{\mathrm{Residual\ Soil}} + N_{\mathrm{Leaching}} + N_{\mathrm{Unaccounted}} \quad [3\text{-}8]$$

$$N_{\mathrm{Loss\ Potential}} = N_{\mathrm{Inputs}} - N_{\mathrm{Plant}} = (1 - \mathrm{NUpE}) \cdot N_{\mathrm{Input}} \quad [3\text{-}9]$$

2.5. N NUTRITION INDEX

Using the measurements of W and N_{Plant}, NNI values at end of season were also calculated (Eq. [3-10]). N nutrition index is used to determine crop N status by comparing actual plant N concentration [$\%N_{\mathrm{Plant}}$] (g N 100 g^{-1} or %N), the ratio of N_{Plant} (kg N ha^{-1}) to W (Mg ha^{-1}) (Eq. [3-11]), to the critical N concentration [$\%N_{\mathrm{Critical}}$] (g N 100 g^{-1} or %N) and as determined by a critical N dilution curve [CNDC] (Eq. [3-12]) (Gastal et al., 2015; Lemaire and Gastal, 1997). Parameter *a* in the CNDC is numerically equivalent to

$\%N_{Critical}$ expressed in units of g N 100 g^{-1} when W is equal to 1 Mg ha^{-1}, but parameters *a* and *b* are both effectively dimensionless. When NNI is greater than 1.0, crop N status is said to be in excess, and crop growth is not limited by N, while when NNI is less than 1.0, crop N status is deficient, and crop growth is limited by N. At NNI equal to 1.0, crop N status is optimal (Lemaire and Gastal, 1997). For this analysis, $\%N_{Critical}$ and NNI were calculated using the CNDC for potato of Ben Abdallah et al. (2016), and parameters *a* and *b* in this CNDC have values of 5.37 and 0.45, respectively. In addition to the robustness of the Ben Abdallah et al. (2016) study (e.g., number of experimental site-years, statistical methods used), this chosen CNDC also matched well with our preliminary data for a CNDC developed for Russet Burbank potato grown in Central Minnesota (*unpublished data*).

Building on the foundation of the CNDC, a critical N uptake curve [CNUC] to determine critical plant N content [$N_{Critical}$] (kg N ha^{-1}) can also be defined (Houlès et al., 2007; Lemaire and Gastal, 1997; Lemaire et al., 2008) by multiplying the CNDC by W (Eq. [3-13]). The parameter *a′* in the CNUC (Eq. [3-13]) is dimensionless but numerically equivalent to 10 times the parameter *a* in the CNDC (Eq. [3-12]) when W is expressed in units of Mg ha^{-1} and when $N_{Critical}$ is expressed in units of kg N ha^{-1}.

$$\mathrm{NNI} = \%\mathrm{N}_{\mathrm{Plant}} \,/\, \%\mathrm{N}_{\mathrm{Critical}} \qquad [3\text{-}10]$$

$$\%\mathrm{N}_{\mathrm{Plant}} = 0.10\ \mathrm{N}_{\mathrm{Plant}} \,/\, \mathrm{W} \qquad [3\text{-}11]$$

$$\%\mathrm{N}_{\mathrm{Critical}} = \mathrm{a}\ \mathrm{W}^{-\mathrm{b}} \qquad [3\text{-}12]$$

$$\mathrm{N}_{\mathrm{Critical}} = \mathrm{a'}\ \mathrm{W}^{(1-\mathrm{b})} = 10\ \mathrm{a}\ \mathrm{W}^{(1-\mathrm{b})} \qquad [3\text{-}13]$$

2.6. RELATING NUE AND NNI

To better interpret NUtE, the concepts of CNDC, CNUC, and NNI can be further expanded. The CNDC and CNUC can be generalized beyond a single critical curve to define curves for any level of plant N status by explicitly including NNI in their calculation (Eqs. [3-14] and [3-15]).

$$\%N_{Plant} = NNI \cdot \%N_{Critical} = NNI \cdot a\,W^{-b} \qquad [3\text{-}14]$$

$$N_{Plant} = NNI \cdot N_{Critical} = NNI \cdot 10\,a\,W^{(1-b)} \qquad [3\text{-}15]$$

Based on these generalized relationships, it becomes apparent that there is an intrinsic relationship between NUtE and NNI. By definition, NUtE is equivalent to the inverse of plant N concentration with an appropriate unit conversion factor to conform to units as previously defined (Eq. [3-16]); therefore, NUtE can be defined using a generalized form of the CNUC (Eq. [3-15]) implying that NUtE depends on NNI, biomass, and the parameters *a* and *b* (Eq. [3-17]). The critical value for NUtE [$NUtE_{Critical}$] for any level of W occurs when NNI is equal to 1.0, in the same manner as $N_{Critical}$ is defined; therefore, $NUtE_{Critical}$ is equivalent to the inverse of the critical N concentration expressed as a ratio, varies as a function of biomass, depends on parameters *a* and *b*, and is defined as the critical N uptake efficiency curve [CNUtEC] (Eq. [3-18]).

$$NUtE = 1000 \cdot W / N_{Plant} = 1000 \cdot (N_{Plant} / W)^{-1} \qquad [3\text{-}16]$$

$$NUtE = 1000 \cdot (NNI \cdot N_{Critical} / W)^{-1} = 1000 \cdot \left(NNI \cdot 10\,a\,W^{-b}\right)^{-1} \qquad [3\text{-}17]$$

$$NUtE_{Critical} = 1000 \cdot (N_{Critical} / W)^{-1} = 1000 \cdot \left(10\,a\,W^{-b}\right)^{-1} \qquad [3\text{-}18]$$

2.7. Statistical analysis

Statistical analysis for response variables of N use efficiency (Eq. [3-4]), N uptake efficiency (Eq. [3-5]), N utilization efficiency (Eq. [3-6]), N nutrition index (Eq. [3-10]), harvest index (Eq. [3-7]), total biomass, and potential N loss (Eq. [3-8]) was conducted using SAS PROC GLIMMIX (SAS Institute, 2013) to test the fixed effects of study year, irrigation treatment, N treatment, and their interactions. The overall significance of each main effect, interaction effect, and of the *a priori* non-orthogonal contrast comparisons for N treatments (Table 3-2) were evaluated for each response variable with significance set at $P < 0.10$. The *a priori* non-orthogonal contrasts were designed to evaluate the effect of control vs. fertilized N treatments (Control), the effect of 180 kg N ha^{-1} vs 270 kg N ha^{-1} (Rate), the effect of PCU vs. split-applied Urea/UAN (Source), and the effect of VR N applied using remote sensing vs. conventional N BMPs (Var. Rate).

3. Results

3.1. Nitrogen balance

Differences in N_{Input} between N treatments originate primarily from differences in applied rate of $N_{Fertilizer}$ (Figure 3-1). However, there was substantial difference in calculated $N_{Mineralization}$ between years with 78 kg N ha^{-1} in 2016 and 144 kg N ha^{-1} in 2017. This supports the findings of the companion studies which suggested lower soil N mineralization in 2016 compared to 2017 as the mechanism behind a significant interaction of the Year and Control N contrast for tuber yield (Bohman et al., 2019) and residual soil nitrate (Bohman et al., 2020). The combined differences in $N_{Mineralization}$, $N_{Irrigation}$, and

$N_{Precipitation}$ observed between years resulted in lower overall N_{Input} in 2016 than in 2017 with 339 and 395 kg N ha^{-1} in each year, respectively.

Differences in N_{Output}, however, originate from differences in $N_{Leaching}$, $N_{Residual\ Soil}$, and N_{Plant} which were reported by Bohman et al. (2020). Essentially, as $N_{Fertilizer}$ increased, N_{Plant} and $N_{Leaching}$ also increased, while $N_{Residual\ Soil}$ did not vary significantly. Significantly less $N_{Leaching}$ was observed in 2016 than in 2017 with 26 and 39 kg N ha^{-1} for each year, respectively. No significant difference in N_{Plant} and $N_{Residual\ Soil}$ was observed between years in the companion study.

There were also differences in $N_{Unaccounted}$ observed between the N treatments. Averaged across Year, $N_{Unaccounted}$ represents a relatively small component of the overall N balance (11–17%) for the fertilized treatments and the value of $N_{Unaccounted}$ increased from or 40–54 kg N ha^{-1}as the value of $N_{Fertilizer}$ increased from 180 to 270 kg N ha^{-1}. However, the exact pathways of loss for $N_{Unaccounted}$ cannot be directly determined due to the limitations of the methodology of this study.

3.2. NITROGEN NUTRITION INDEX

Nitrogen nutrition index values varied significantly by N treatment, with NNI increasing as N fertilizer rate increased (Table 3-3). The Control treatment had significantly lower NNI (0.520) than the fertilized treatments (0.892), and the 180 N treatments had significantly lower NNI (0.806) than the 270 N treatments (0.979). There was also a significant interaction between the Variable Rate N contrast and Year where the 270 N treatments had similar NNI in both 2016 (0.969) and 2017 (0.989), while the VR Split treatment had higher NNI in 2016 (0.934) than in 2017 (0.847). The reduced NNI values for the VR Split treatment were likely caused by the reduction in applied N fertilizer rate of 22 kg N ha^{-1} and 44 kg N ha^{-1} for the VR Split relative to the 270 N treatments, with reduction in NNI occurring with reduction in N fertilizer rate. Irrigation was not found to have a significant effect on NNI (Table 3-3). Based on theoretical optimal NNI value of 1.0, end-of-season crop N status was sufficient in the 270 N treatments, marginally deficient in the VR Split treatment, and deficient in the Control and 180 N treatments.

3.3. Biomass and harvest index

Biomass productivity increased as N rate increased (Table 3-3). The Control N treatment had significantly lower biomass (12.0 Mg ha^{-1}) than the other fertilized treatments (17.4 Mg ha^{-1}), and biomass increased significantly from 16.7–17.8 Mg ha^{-1} as N rate increased from 180 to 270 kg N ha^{-1}. Except for the VR Split treatment, which had similar biomass production as the 270 N treatment, biomass was observed to increase as end-of-season NNI increased. The lack of a significant difference in biomass production between the VR Split and 270 N treatments suggests that N stress only occurred in the VR Split treatment at the end of the growing season and the crop N status in VR Split was otherwise sufficient. The Year and Control N contrast interaction was significant with significantly lower biomass in the Control N treatment in 2016 (11.4 Mg ha^{-1}) than 2017 (12.6 Mg ha^{-1}), while biomass in the fertilized N treatments was equivalent in both 2016 and 2017 (17.4 Mg ha^{-1}). The Year and Source N contrast interaction was significant with the Urea/UAN treatments decreasing from 2016 (17.7 Mg ha^{-1}) to 2017 (17.0 Mg ha^{-1}), while the ESN treatments increased from 2016 (16.9 Mg ha^{-1}) to 2017 (17.3 Mg ha^{-1}). Irrigation did not have a significant effect on biomass production.

Harvest index had a similar response to N as biomass, but in the opposite direction (Table 3-3). As N rate increased, HI was observed to decrease. The Control N treatment had significantly greater HI (0.935) than the other fertilized treatments (0.864), and HI decreased as the rate of N applied increased from 180 to 270 kg N ha^{-1}; however, the Year and Rate N contrast was significant with similar HI for the 270 N treatments between 2016 (0.854) and 2017 (0.852) while HI decreased for the 180 N treatments between 2016 (0.898) and 2017 (0.861). The Year and Variable Rate N contrast interaction was also significant, with greater HI for the VR Split treatment in 2016 (0.876) than 2017 (0.833), while the 270 N treatments, as previously described, were similar between years. These findings can be explained by the occurrence of crop N stress (i.e., end-of-season NNI much lower than 1.0) in the 180 N and Control N treatments, leading to earlier initiation of vine senescence and a relatively greater HI for the 270 N and VR Split treatments. Additionally, these findings indicate that both environmental conditions and management practices (i.e., timing of planting and harvest) can result in variations in HI. Irrigation treatment did not significantly affect HI.

3.4. Nitrogen uptake efficiency

Nitrogen uptake efficiency varied significantly by both Year and N treatment but was not significantly affected by Irrigation treatment (Table 3-3). There was a significant difference in NUpE observed between the Control N treatment (0.505 g N g^{-1} N) and the other fertilized N treatments (0.576 g N g^{-1} N), while there were no significant differences in NUpE among the treatments fertilized after planting (Table 3-3). Therefore, the differences in plant N uptake for the N treatments fertilized after planting directly result from differences in total N inputs (Figure 3-1), which includes differences in N fertilizer rate, rather than from differences in NUpE. The reduced NUpE for the Control N treatment, with an end-of-season NNI value of 0.520, was likely limited by poor crop and root growth, which ultimately lead to poor crop N uptake relative to the other fertilized treatments. With end-of-season NNI values ranging between 0.801 to 0.985, it is likely that NUpE in the N treatments fertilized after planting was not limited by poor crop growth. Similarly, the NUpE in the fertilized N treatments was likely not limited by maximum N uptake capacity, which occurs under conditions when NNI is much greater than one (Gastal et al., 2015).

Nitrogen uptake efficiency was greater in 2016 than in 2017 with values of 0.602 and 0.526 g N g^{-1} N, respectively (Table 3-3). This effect was likely caused by lower soil N mineralization in 2016 (78 kg N ha-) compared to 2017 (144 kg N ha^{-1}). Nitrate leaching losses reported in the companion paper (Bohman et al., 2020) were also greater in 2017 (39 kg N ha^{-1}) than in 2016 (26 kg N ha^{-1}), which could also explain the reduced NUpE value in 2017. Environmental or management conditions that increase soil N losses will result in reduced NUpE (Bock, 1984). Because management practices were similar each year, the presence of a significant effect of Year suggests that environmental conditions (e.g., soil N mineralization, N leaching losses, etc.) were the most important factors affecting NUpE in this study. However, it appears that within the environmental conditions of a given year that the source and timing of N fertilizer management practices evaluated in this study for the non-Control N treatments are sufficient in terms of maximizing NUpE.

3.5. Potential N losses

Potential N loss was lower in 2016 (135 kg N ha^{-1}) than 2017 (187 kg N ha^{-1}) due to both greater NUpE and lower N_{Input} in 2016 (0.602 g N g^{-1} N and 339 kg N ha^{-1}, respectively) than in 2017 (0.526 g N g^{-1} N and 395 kg N ha^{-1}, respectively). This finding of variation in $N_{Loss\ Potential}$ by Year reinforces that N losses in potato production cannot be entirely controlled for by N fertilizer management, and environmental conditions are an important factor that determine the extent to which environmental N loss occurs.

To reduce $N_{Loss\ Potential}$ on an absolute basis, either NUpE must increase or N_{Input} must decrease (Eq. [9]), and the data from this study illustrates this relationship (Figure 3-2, Table 3-3). For the fertilized N treatments all having similar values of NUpE (0.576 g N g N^{-1}), $N_{Loss\ Potential}$ averaged over Year increased from 150 to 191 kg N ha^{-1} as N_{Input} increased from 355 to 445 kg N ha^{-1}. Notably, the VR Split treatment, which reduced $N_{Fertilizer}$ by 22 and 44 kg N ha^{-1} in 2016 and 2017, respectively, reduced $N_{Loss\ Potential}$ by 10 kg N ha^{-1} in each year relative to the N treatments receiving 270 kg N ha^{-1}. While the control N treatment had the lowest $N_{Loss\ Potential}$ (110 kg N ha^{-1}), the lower NUpE for this treatment (0.505 g N g^{-1} N) compared to the fertilized treatments (0.576 g N g^{-1} N) resulted in greater $N_{Loss\ Potential}$ than would have been expected for the same level of N_{Input} without a reduction in NUpE (Figure 3-2).

3.6. Nitrogen utilization efficiency and relationships with NNI

The response of NUtE to N treatment had a similar pattern to the responses for NNI, but the response for NUtE occurred in the opposite direction found for NNI (Table 3-3). Overall, as total N rate increased in the present study, NUtE decreased significantly. The Control N treatment had significantly greater NUtE (109.8 g g^{-1} N) than the fertilized treatments (76.3 g g^{-1} N). The 180 N treatments had significantly greater NUtE (82.6 g g^{-1} N) than the 270 N treatments (69.7 g g^{-1} N). There was a significant interaction between the Variable Rate N contrast and Year where the 270 N treatments had similar NUtE in both 2016 (70.8 g g^{-1} N) and 2017 (68.5 g g^{-1} N), while the VR Split treatment had lower NUtE in 2016 (72.8 g g^{-1} N) than in 2017 (81.2 g g^{-1} N). This increase in NUtE is explained in the same manner used for the effect of this interaction on NNI. The additional 22 kg N ha^{-1} of $N_{Fertilizer}$ applied in 2016 relative to 2017 for VR Split resulted in greater N_{Plant}, because NUpE for VR Split did not vary between years. Because biomass for VR Split did not vary between years, this resulted in reduced NUtE for 2016 relative to 2017. Irrigation was found to not have a significant effect on NUtE in the present study.

The relationship between $\%N_{Plant}$ and biomass at a constant value of NNI is non-linear (Figure 3-3a). As NNI varies at a given level of biomass, then $\%N_{Plant}$ varies in a manner directly proportional to NNI (Eq. [3-14]). This figure also clearly demonstrates the fundamental relationship between biomass, $\%N_{Plant}$, and NNI. Biomass production is limited when $\%N_{Plant}$ is less than $\%N_{Critical}$ (i.e., NNI < 1.0), which can be observed with the Control N treatment having the lowest values for $\%N_{Plant}$, end-of-season NNI, and biomass, and the 270 Split and 270 CR treatments having the greatest values for $\%N_{Plant}$, end-of-season NNI, and biomass (Figure 3-3a).

Similarly, the relationship between N_{Plant} and biomass at a constant value of NNI is non-linear (Figure 3-3b), where N_{Plant} varies in a manner directly proportional to NNI (Eq. [3-15]). The N_{Plant} and biomass relationship and $\%N_{Plant}$ and biomass relationship can be interpreted similarly, because they represent the same type of dilution phenomenon (i.e., CNDC and CNUC) simply presented using different units (i.e., N concentration [g N 100 g^{-1}] vs. N content [kg N ha^{-1}]).

The relationship between NUtE and biomass at a constant value of NNI is also non-linear (Figure 3-3c). In this case, however, NUtE is inversely proportional to NNI (Eq. [3-17]). As NNI decreases at a given level of biomass, then NUtE subsequently increases. The greater value of NUtE (109.8) observed for the Control N treatment is related to a reduction in end-of-season NNI (0.544). Similarly, the relatively lower value of NUtE for the 270 Split and 270 CR treatments (69.7) is related to the greater value of end-of-season NNI (1.029) observed for these treatments.

The NUtE, NNI, and biomass relationship has two important properties. First, for a constant value of NNI, NUtE increases as biomass increases, which implies that NUtE can vary without any change in crop N status (i.e., change in NNI). Second, when NUtE increases at a constant value of biomass, NNI necessarily decreases. An increasing value of NUtE in this case of constant biomass represents an increase in crop N stress, which will result in reduced agronomic production. Stated differently, any increase in NUtE that is not associated with an increase in biomass will result in a decrease in NNI and an increase in crop N stress. Therefore, the theoretical quantitative relationship identified in this study (i.e., CNUtEC) provides the NUtE value (i.e., $NUtE_{Critical}$) which delineates between stressed and non-stressed conditions on the basis biomass and in the context of the NNI framework (i.e., Eq. [3-18]). Because NUtE values greater than $NUtE_{Critical}$ represent crop N stress, attempting to maximize NUtE without respect to biomass will lead to reduced agronomic production.

3.7. Nitrogen use efficiency

Because NUE is defined as the product of NUpE, NUtE, and HI, it is understandable that the response of NUE to the experimental treatments reflects the response of the component parts. Nitrogen use efficiency was found to vary significantly by Year with a value of 43.4 g g^{-1} N in 2016 and 36.8 g g^{-1} N in 2017 (Table 3-3). This is the result of both NUpE and HI having significantly greater values in 2016 (0.602 g N g^{-1} N and 0.887 g g^{-1}, respectively) than in 2017 (0.526 g N g^{-1} N and 0.865 g g^{-1}, respectively). Nitrogen treatment also had a significant effect on NUE (Table 3-3). The N treatments fertilized after planting had significantly lower NUE than the Control N treatment (37.8 g g^{-1} N vs. 51.6 g g^{-1} N). This effect resulted from the Control N treatment having significantly lower NUpE (0.505 g N g^{-1} N) and significantly greater NUtE and HI (109.8 g g^{-1} N and 0.935 g g^{-1}, respectively) compared with the fertilized treatments (0.576 g N g^{-1} N, 76.3 g g^{-1} N, and 0.864 g g^{-1}, respectively). Similarly, NUE in the 180 kg N ha^{-1} treatments (41.6 g g^{-1} N) was greater than in the 270 kg N ha^{-1} treatments (34.3 g g^{-1} N), resulting from a significantly greater NUtE and HI for the 180 N treatments (82.6 g g^{-1} N and 0.880 g g^{-1}, respectively) compared to the 270 N treatments (69.7 g g^{-1} N and 0.853 g g^{-1}, respectively). Finally, NUE in the VR Split treatment (37.3 g g^{-1} N) was significantly greater than in the 270 N treatments (34.3 g g^{-1} N), as a result of significantly greater NUtE for the VR Split treatment (77.0 g g^{-1} N) compared to the 270 N treatments (69.7 g g^{-1} N). The interaction effect for the Year x Control N contrast was significant for NUE. Interpreting the relatively greater change in magnitude of NUE between 2016 and 2017 for Control N (56.2 and 47.0 g g^{-1}, respectively) relative to the other fertilized N treatments (40.9 and 34.7 g g^{-1}, respectively) is difficult because this same contrast interaction effect was found not to be significant for either NUpE, NUtE, or HI (Table 3-3). Irrigation did not have a significant effect on NUE, which is expected because Irrigation did not have a significant effect on NUpE, NUtE, or HI.

4. Discussion

4.1. Limitations of the nitrogen balance method

While the methods used to calculate the N balance in this study attempted to reasonably account for all possible pathways, sources, and sinks of N, the limitations of the methods used resulted in a negative value for $N_{Unaccounted}$ (i.e., measured N_{Output} less than measured N_{Input}). This indicates that either 1) N_{Output} is underestimated or 2) N_{Input} is overestimated. Understanding the mechanisms for and implications of each plausible sources of $N_{Unaccounted}$ is important for interpreting the findings of this study.

4.1.1. Underestimated N_{Output}

One source for underestimation of N_{Output} is the lack of direct measurement of gaseous N losses. Gaseous emissions of N_2O measured from studies on potato conducted at the same location as the current study are of a magnitude of 1–2 kg N ha^{-1} (Souza et al., 2019; Venterea et al., 2011), and losses of other oxidized gaseous N species (e.g., NO) are likely less than this (Fujinuma et al., 2011). Gaseous losses of NH_3 are also likely low due to the slightly acid pH of this sandy soil and immediate incorporation of granular urea and PCU fertilizer following application. Dinitrogen gas is another plausible source of gaseous N loss and based on a reasonable estimate of 0.2 for $N_2O/(N_2O + N_2)$ (Gillam et al., 2008), the magnitude of N_2 emissions was likely on the order of less than 10 kg N ha^{-1}.

Another source for underestimation of N_{Output} is the limitations of the suction cup lysimeters method used to measure $N_{Leaching}$ in this study. While suction cup lysimeters are capable of detecting relative differences in nitrate concentration in the soil solution between experimental treatments, this method can be subject to error in calculating nitrate leaching load due to the indirect method necessary to calculate percolation (e.g., via soil moisture balance calculation) ((Lord and Shepherd, 1993; Singh et al., 2017). Additionally, the potential for preferential flow paths in sandy soils (Kung, 1990) presents another limitation of the suction cup lysimeter method for collecting a representative measurement of nitrate concentration in the soil solution.

Finally, while suction cup lysimeters were installed at a depth of 120 cm, initial and residual soil inorganic N measurements were only collected to a depth of 60 cm. This leaves open the possibility that changes in soil inorganic N between 60 and 120 cm depth could also be a meaningful component of $N_{Unaccounted}$.

Overall, it is plausible that total gaseous N losses, underestimation of nitrate leaching losses, and changes in soil inorganic nitrogen between 60 and 120 cm could approach the magnitude of $N_{Unaccounted}$ observed in this study. If $N_{Unaccounted}$ in this study was simply due to underestimation of N_{Output}, rather than an overestimation of N_{Input}, then there would be no impact on either absolute or relative values for NUpE, NUE, and $N_{Loss\ Potential}$ or on their subsequent interpretation. However, in this scenario the directly measured environmental impacts of potato production (e.g., greenhouse gas emissions, nitrate leaching, etc.) would be underestimated, which has meaningful implications for using the results of this study for informing management and policy decisions.

4.1.2. Overestimated N_{Input}

Another possible source of the observed $N_{Unaccounted}$ is an overestimation of N_{Input} due to differential $N_{Mineralization}$ between the various N treatments – namely, it is plausible that the limitations of the N balance methods used in this study could have overestimated $N_{Mineralization}$ in the fertilized N treatment. If $N_{Unaccounted}$ is the result of between treatment differences in $N_{Mineralization}$, then this would violate a key assumption of the "difference" method that $N_{Mineralization}$ for all fertilized N treatments is equal to that calculated for the unfertilized N treatment. Additionally, the directionality of this potential error is opposed to the conventional understanding of the "priming" effect where the addition of N fertilizer results in greater $N_{Mineralization}$ than unfertilized conditions (Cassman et al., 2002; Gardner and Drinkwater, 2009; Jansson and Persson, 1982). However, recent work by (Mahal et al., 2019) refutes the "priming" effect and found that gross ammonification is suppressed by N fertilizer applications with the "difference" method in fact likely to overestimate $N_{Mineralization}$ under fertilized conditions especially in soils with low organic matter.

Two additional considerations provide some support for the relevance of the (Mahal et al., 2019) hypothesis for understanding the limitations of the N balance of the present study. First, the finding that the value of $N_{Unaccounted}$ increased as $N_{Fertilizer}$ increased provides some circumstantial evidence that increasing $N_{Fertilzer}$ may be correlated with decreasing $N_{Mineralization}$ (e.g., due to reduction in gross mineralization). Second, while residues from the previously grown rye crop would have had a high C/N ratio, the management practices used to harvest the rye (e.g., removing both grain and stalks) limited the potential for the potential occurrence of a "priming" effect on $N_{Mineralization}$ in fertilized N treatments.

If $N_{Mineralization}$ is in fact overestimated for the fertilized N treatments in this study, then the respective values of NUpE and NUE would be underestimated, while the value of $N_{Loss\ Potential}$ would be overestimated due to both the resulting overestimation of N_{Input} and underestimation of NUpE. Therefore, the significant difference in NUpE observed between Control N and Fertilized N treatments in this study likely represent true physiological differences in plant N uptake rather than just a numerical artifact of the N balance method used in this study. Future research is needed to better understand differences in mineralization between fertilized and non-fertilized conditions and the resulting effect on NUpE, NUE, and $N_{Loss\ Potential}$.

4.2. Limitations of N nutrition index and critical N dilution curves

There have been at least 5 CNDCs developed for potato (Chen et al., 2021); therefore, it can be difficult to identify which if any CNDC is most appropriate to use in the context of a particular geography and cropping system. While a broader analysis evaluating the full set of CNDCs for potato is needed to fully discuss this subject, two recent studies provide helpful tools to help understand how to interpret the differences in CNDCs and how this impacts interpretation of NUtE and NUE.

First, Makowski et al. (2020) developed a new statistical method for developing CNDCs from experimental data without the need for separate, explicit identification of critical N points and to also account for uncertainty in the value of CNDC parameters. While this new method produces results equally as valid as the conventional approach, having a more flexible and generic statistical method that could be applied to existing data sets will remove another barrier in interpreting differences between CNDCs produced from different studies.

Second, Giletto et al. (2020) developed separate CNDCs for both vines and tubers and identified that the pattern of whole plant N dilution in potatoes is due to both the allometric decline of N concentration in shoots and tubers and the relative increase in the proportion of biomass in low N concentration tissues (e.g., tubers). Additionally, the results of the Giletto et al. (2020) study suggest that differences in whole plant N dilution between potato varieties are the result of differential partitioning of biomass to tubers. Therefore, identifying the appropriate CNDC for a given potato variety should include evaluation based on the pattern of biomass partitioning between vines and tubers.

The particular values for both NNI and $NUtE_{Critical}$ presented in this study are inherently subject to the limitations of the appropriateness of the CNDC from Ben Abdullah et al. (2016) chosen for use in our analysis. In future studies, using a CNDC curve with explicitly quantified uncertainty (e.g., Makowski et al., 2020) would allow for calculation of subsequent uncertainty in NNI and $NUtE_{Critical}$. For example, it may be more appropriate to report and interpret both NNI and $NUtE_{Critical}$ as a distribution of values rather than as a singular value. Additionally, development of a CNDC for potato grown in Central Minnesota, USA is in progress as a subsequent study.

4.3. Previous studies on N use efficiency for potato

Most previous studies on potato have not explicitly accounted for NNI when evaluating NUE. Other past studies evaluated NUE for potato including Kleinkopf et al. (1981); Errebhi et al. (1998b), and Errebhi et al. (1999). However, these studies did not calculate NUpE, NUtE, and NNI in the same manner as used in the present study with the differences in methodology in part due to differences in study objectives.

Zebarth et al. (2004) evaluated NUpE, and NUtE for 20 potato varieties ranging in maturity class and grown in New Brunswick, Canada on non-irrigated plots. In general, this study found that as N rate increased from 0 to 100 kg N ha^{-1}, NUtE decreased significantly from 116 to 81 g g^{-1} N. Their study also found that NUpE slightly decreased from 0.75 to 0.68 g N g^{-1} N as N rate increased. There was significant variation observed by Zebarth et al. (2004) among cultivars evaluated for both NUpE and NUtE. Total biomass and harvest index were also reported in their previous study. As N rate increased, total biomass increased from 9.3–11.7 Mg ha^{-1} while harvest index decreased from 0.84 to 0.80. Total biomass and harvest index were also found to vary significantly by variety and year.

Maltas et al. (2018) evaluated NUpE and NUtE for Bintje and Laura potato varieties grown in Switzerland on irrigated plots. Nitrogen nutrition index values were reported in this study and used in a qualitative manner to explain the observed decrease in both NUtE and NUpE as N rate increased. As N rate increased from 120 to 200 kg N ha^{-1}, NNI measured at 80 days after planting increased from 1.19 to 1.27. This corresponds with a decrease in both NUtE and NUpE measured at harvest from 85 to 75 g g^{-1} N and 1.43 to 0.95 g N g^{-1} N, respectively. Overall, there were no significant differences in NUpE and NUtE among varieties evaluated in the Maltas et al. (2018) study. Total biomass was found not to significantly vary as N rate increased, and harvest index was not reported.

Overall, when crop N status and biomass (i.e., NNI and $NUtE_{Critical}$) are not considered when interpreting NUE and its constituent parts, it is difficult to identify whether environmental conditions, genotype, or management practices are the source of observed differences (Sadras and Lemaire, 2014).

4.4. Interpreting N use efficiency

Similar to the approach commonly used in the interpretation of interaction effects in a statistical analysis (Vargas et al., 2015), it is most appropriate to interpret NUE in terms of its component factors (i.e., NUpE, NUtE, and HI) rather than as an aggregated factor. The physiological meaning, agronomic and environmental outcomes, and implications for management practices are not easily discernable in the aggregated form of NUE. Therefore, interpreting NUE requires separate interpretation of NUpE, NUtE, and HI.

Interpreting NUtE in terms of desired agronomic outcomes (i.e., biomass production) requires explicit quantification of crop N status (i.e., NNI). It is not possible to characterize the source of variation in NUtE without accounting for both NNI and biomass, and experiments that fully control for crop biomass and N status (i.e., NNI) in their evaluation of NUtE have not been previously conducted (Gastal et al., 2015). To our knowledge, the present study is the first attempt to explicitly define and utilize a quantitative theoretical relationship to account for NNI in the interpretation of NUtE and NUE. The relationship presented in the present study between NUtE, NNI, and biomass (Eq. [3-17]) has not been explicitly derived previously, and the identification of a $NUtE_{Critical}$ value using the CNUtEC (Eq. [3-18]) is also novel. Previous studies, however, have alluded to various components of this relationship (Barraclough et al., 2010; Gastal et al., 2015; Sadras and Lemaire, 2014; Caviglia et al., 2014). The contribution of this study to the previously established theoretical framework is the explicit formulation of the CNUtEC which provides an explicit method to relate NUE and NUtE to the NNI framework using the CNDC parameters.

Additionally, comparisons of NUtE made across genotype, environmental, and management conditions (e.g., Lemaire and Ciampitti, 2020) require consideration of the relationship between NUtE, NNI, and biomass either explicitly (e.g., Eq. [3-17]) or implicitly by restricting comparisons only to conditions with equivalent or similar levels of biomass. Proper interpretation and comparisons of the variation in NUtE and NUE requires considering and controlling for both NNI and biomass.

Interpreting NUpE in terms of environmental impacts (i.e., potential N losses) requires explicit quantification of all N inputs (i.e., fertilizer N, soil N mineralization, etc.). When NUpE is estimated based only on fertilizer N inputs, the value of NUpE is over-estimated; however, relative differences in NUpE between treatments can still be determined if using a control treatment to account for variation in N uptake due to mineralization. Variation in soil N mineralization between years and between N management practices is also important in determining potential N losses by directly affecting N inputs and indirectly affecting NUpE. This allows for assessment of the effectiveness of management practices at mitigating losses of N to the environment within the context of a given set of environmental conditions. Previous studies have identified a theoretical Michaelis-Menten type relationship between optimal crop N status and the rate of N uptake, where for any given level of soil nitrate concentration, relative crop growth rate and nitrate uptake rate are maximized when NNI is greater than or equal to 1.0 (Devienne-Barret (2000); Sadras and Lemaire, 2014).

Interpreting HI for potato is challenging to do for indeterminate potato varieties. Under conditions of sufficient N (i.e., NNI ≥ 1.0), leaf area index [LAI] will be maintained at its maximum value. Once crop N status becomes deficient (i.e., NNI < 1), LAI will begin to decrease resulting in an increase in HI as nutrients are translocated from vines to tubers (Duchenne et al., 1997; Dyson and Watson, 1971; Gastal et al., 2015; Zhou et al., 2017; Bélanger et al., 2001a,b; Kleinkopf et al., 1981; Millard and Marshall, 1986). Harvest index can also vary substantially based on management practices other than N applications (e.g., planting and harvest date) and on environmental conditions (Allen and Scott, 1980; Mackerron and Heilbronn, 1985; Millard and Marshall, 1986). This makes tuber yield response to N more difficult to interpret than biomass response to N. Overall, HI is determined by the complex interaction of crop N status, environmental factors (e.g., solar radiation and temperature, etc.), cultural management practices (e.g., fertilizer rate, pest control, length of growing season, etc.), genotype (e.g., variety), and management to meet market demands (e.g., ideal tuber size, quality, storability, etc.) (Ewing and Struik, 1992; Haverkort and Struik, 2015; Kooman et al., 1996a, b; Van Der Zaag and Doornbos, 1987).

4.5. Improving N use efficiency

Fundamental improvements in NUpE, NUtE, and NUE will require system changes beyond N management practices alone. Reduction in potential N losses beyond what is possible when NUpE is maximized by maintaining NNI at a value of 1.0 will necessarily result in changes in cropping systems rather than in N management practices. This includes diversifying crop rotations to include crops with high NUpE and low potential for N losses such as alfalfa (Randall and Mulla, 2001) or perennial intermediate wheat grass (Jungers et al., 2019), planting cover crops following potato to recover residual soil N (Shipley et al., 1992), or using potato varieties with greater NUpE resulting from an improved rooting structure and N uptake capacity (Garnett et al., 2009; Tiwari et al., 2018).

Efforts to improve NUtE in potato via crop breeding should focus on decreasing the critical N concentration (i.e., by affecting the parameters of the CNDC). In general, lowering the N concentration of storage tissues (e.g., grain and tubers) will reduce critical N concentration (Lemaire and Gastal, 1997) and subsequently increase the critical value of NUtE. However, this change in $\%N_{Critical}$ would occur at the expense of increasing starch and sugar concentration and reducing protein, which may not be a desirable outcome for nutritional quality. In particular, the findings of Giletto et al. (2020) directly suggest that selecting for varieties that partition a greater proportion of biomass to tubers will have lower $\%N_{Critical}$ and result in a increased value for $NUtE_{Critical}$. Additionally, efforts to introduce improved metabolic pathways into C_3 crops, such as potato, would also fundamentally improve NUtE by reducing critical N concentration through improving photosynthetic productivity and decreasing specific leaf N concentration (Garnett et al., 2015; South et al., 2019).

5. Conclusions

The commonly stated goal of maximizing NUE will not necessarily achieve desired agronomic and environmental outcomes unless both crop N status and biomass are explicitly considered using a quantitative theoretical relationship (i.e., CNUtEC). In general, NUE and NUtE are substantially increased while NUpE and HI are slightly decreased, as crop N stress increases (i.e., as NNI decreases). Therefore, maximizing NUE does not necessarily improve agronomic and environmental outcomes for potato. The findings of the present study, in the context of previous studies, indicate implementing N and irrigation management practices that maintain crop N status at an NNI value of 1.0 is one plausible approach to manage the tradeoffs between both agronomic production (i.e., NUtE and HI) and losses of N to the environment (i.e., NUpE, N_{Input}). Using the NNI framework allows for improved interpretation of agronomic outcomes, environmental impacts, and NUE for potato.

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FIGURES

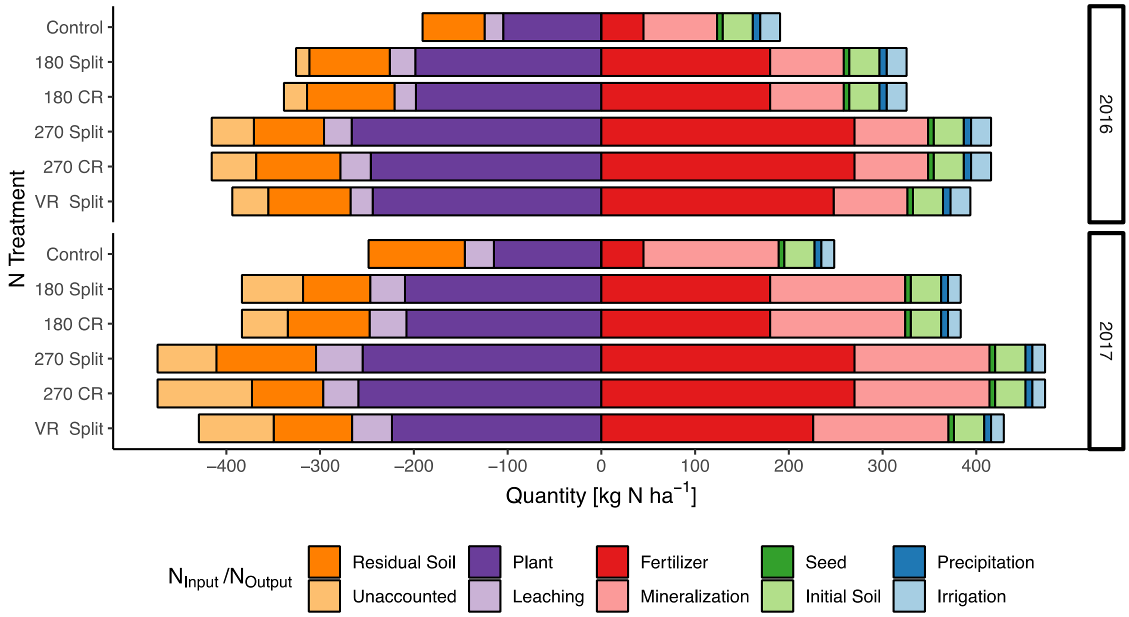


Figure 3-1. Components of N input [N_{Input}] and N output [N_{Output}] shown for each Year and each N treatment averaged over Irrigation treatment, including all inputs and outputs of N identified in Eqs. [3-1], [3-2], and [3-3].

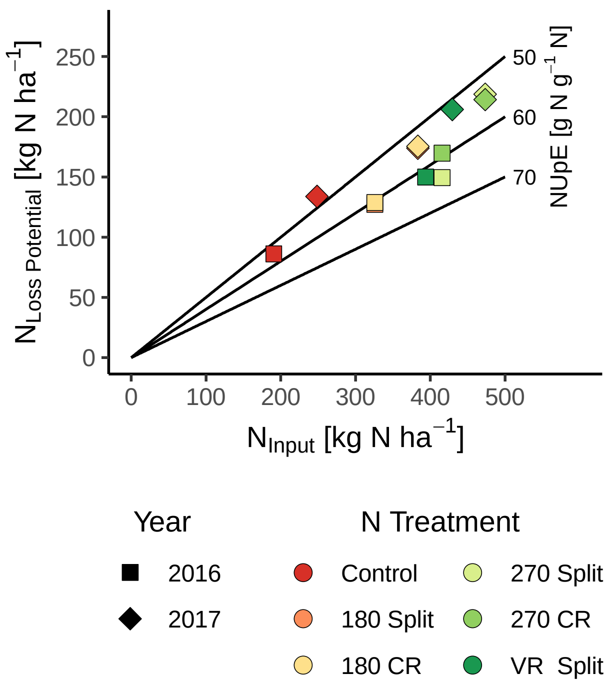
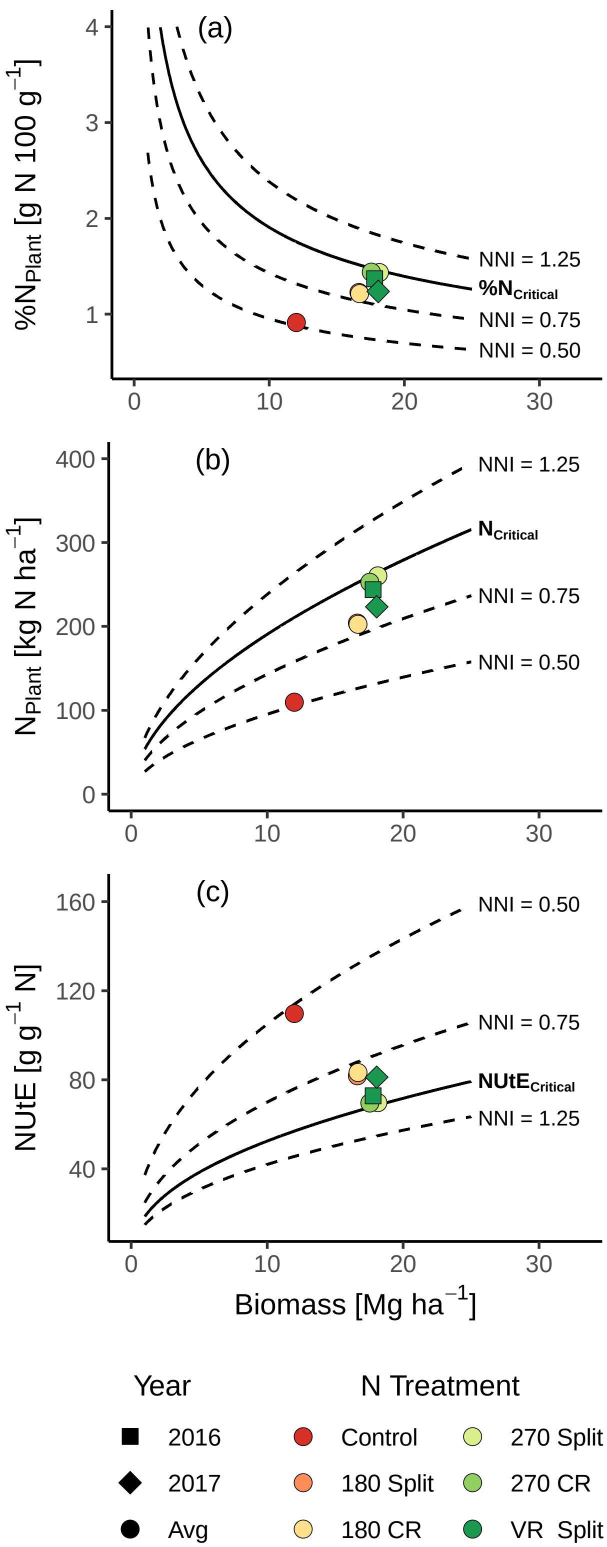


Figure 3-2. Relationship between N input [N_{Input}] and potential N losses [$N_{Potential\ Loss}$] with N uptake efficiency [NUpE] represented by the slope of the solid line based on Eq. [3-9]. Points shown for the mean value for the N treatment x Year interaction with N treatment represented by color and Year represented by shape.



(a)
%N_Plant [g N 100 g^-1]
NNI = 1.25
%N_Critical
NNI = 0.75
NNI = 0.50
(b)
N_Plant [kg N ha^-1]
NNI = 1.25
N_Critical
NNI = 0.75
NNI = 0.50
(c)
NUtE [g g^-1 N]
NNI = 0.50
NNI = 0.75
NUtE_Critical
NNI = 1.25
Biomass [Mg ha^-1]
Year
2016
2017
Avg
N Treatment
Control
180 Split
180 CR
270 Split
270 CR
VR Split

Figure 3-3. Quantitative theoretical relationships between (a) plant N concentration [$\%N_{Plant}$], (b) plant N uptake [N_{Plant}], and (c) N utilization efficiency [NUtE] with whole plant d.w. biomass [W]. The solid line in each figure represents (a) the critical N dilution curve [CNDC] (Eq. [3-12]), (b) the critical N uptake curve [CNUC] (Eq. [3-13]), and (c) the critical N utilization efficiency curve [CNUtEC] (Eq. [3-18]), based on the parameters reported by Ben Abdallah et al. (2016). The dashed lines show the value for (a) $\%N_{Plant}$ (Eq. [14]), (b) N_{Plant} (Eq. [3-15]), (c) NUtE (Eq. [3-17]) at a constant N nutrition index [NNI] value as indicated in the figure (e.g., NNI equal to 0.50, 0.75, or 1.25). The points displayed represent end-of-season measurements for the main effect of N treatment, averaged over levels of Year and Irrigation treatment, except for the points representing the VR Split N treatment which are presented separately for each Year and averaged over Irrigation treatment to show the significant interaction effect for the Year x Variable Rate N contrast.

TABLES

Table 3-1. Rate, source, and timing of experimental nitrogen treatments

	Planting	Emergence	Post-Emergence				Total
2016	22 Apr	1 June	23 June	14 July	21 July	27 July	
2017	29 Apr	30 May	28 June	10 July	20 July	27 July	
	kg N ha^{-1}						
Control	45 DAP†	-	-	-	-	-	45
180 Split	45 DAP	67 Urea	17 UAN	17 UAN†	17 UAN	17 UAN	180
180 CR	45 DAP	135 PCU	-	-	-	-	180
270 Split	45 DAP	135 Urea	22 UAN	22 UAN	22 UAN	22 UAN	270
270 CR	45 DAP	225 PCU†	-	-	-	-	270
VR Split (2016)	45 DAP	135 Urea	-	22 UAN	22 UAN	22 UAN	248
VR Split (2017)	45 DAP	135 Urea	-	22 UAN	-	22 UAN	226

† Diammonium phosphate [DAP], urea/ammonium nitrate [UAN], and polymer-coated urea [PCU].

Table 3-2. Non-orthogonal contrasts used for *a priori* hypothesis testing on N treatments.

	Control	180 Split	180 CR†	270 Split	270 CR	VR Split
Control	-5	+1	+1	+1	+1	+1
Rate	0	-1	-1	+1	+1	0
Source	0	-1	+1	-1	+1	0
Var. Rate	0	0	0	-1	-1	2

Table 3-3. Mean values and analysis of variance for N uptake efficiency, potential N losses, N utilization efficiency, N nutrition index, total biomass, harvest index, and N use efficiency.

Mean Values	NNI	Biomass	HI	NUpE	Potential N Loss	NUtE	NUE
Year	–	Mg ha^{-1}	g g^{-1}	g N g^{-1} N	kg N ha^{-1}	g g^{-1} N	g g^{-1} N
2016	0.826	16.4	0.887	0.602	135	82.0	43.4
2017	0.834	16.6	0.865	0.526	187	81.8	36.8
Irrigation							
Reduced	0.832	16.5	0.875	0.568	158	81.9	40.2
Convent.	0.828	16.4	0.876	0.561	164	81.8	40.0
Nitrogen							
Control	0.520	12.0	0.935	0.505	110	109.8	51.6
180 Split	0.810	16.6	0.881	0.578	151	81.9	41.7
180 CR	0.801	16.7	0.878	0.573	152	83.3	41.4
270 Split	0.985	18.1	0.850	0.589	184	69.7	34.7
270 CR	0.973	17.5	0.856	0.570	192	69.6	33.9
VR Split	0.891	17.9	0.855	0.570	178	77.0	37.3
ANOVA	NNI	Biomass	HI	NUpE	Potential N Loss	NUtE	NUE
Year [Y]	–	–	+	*†	***	–	**
Irrigation [I]	–	–	–	–	–	–	–
Nitrogen [N]	***	***	***	***	***	***	***
Control‡	***	***	***	***	***	***	***
Rate	***	***	**	–	***	***	***
Source	–	–	–	–	–	–	–
Var. Rate	***	–	–	–	+	***	**
I x N	–	–	–	–	–	–	–
Y x I	–	–	–	–	–	–	–
Y x N	*	–	*	–	–	–	–
Y x Control	–	+	–	–	–	–	+
Y x Rate	–	–	+	–	–	–	–
Y x Source	–	+	–	–	–	–	–
Y x Var. Rate	**	–	+	–	–	**	–
Y x I x N	–	–	–	–	–	–	–

† ***, **, *, and + denote significance at the α = 0.001, 0.01, 0.05, and 0.10 levels, respectively. – indicates a non-significant effect.

‡ A priori non-orthogonal contrast, as specified in Table 3-2

CHAPTER 4 – QUANTIFYING THE UNCERTAINTY IN CRITICAL N CONCENTRATION FOR POTATO USING BAYESIAN METHODS

This chapter is being prepared for submission to Plants – Special Issue "Improving Nitrogen-Use Efficiency at the Cropping System Scale: Agronomic and Genetic Aspects"

Bohman, B.J., M.J. Culshaw-Maurer, F. Ben Abdallah, C. Giletto, G. Bélanger, F.G. Fernández, Y. Miao, D.J. Mulla, and C.J. Rosen. (2021). Quantifying the uncertainty in critical N concentration for potato using Bayesian methods. Plants. (*in preparation*).

ABSTRACT

Multiple critical N dilution curves [CNDCs] have been previously developed for potato; however, attempts to directly compare differences in CNDCs across genotype [G] and environment [E] interactions have been confounded by non-uniform statistical methods and lack of proper quantification of uncertainty in critical N concentration [$\%N_c$]. This study implements a hierarchical Bayesian framework to develop CNDCs for previously published and newly reported experimental data, systematically evaluates the difference in $\%N_c$ across G x E effects, and directly compares CNDCs from the Bayesian framework to CNDCs from conventional statistical methods. Differences in $\%N_c$ were primarily the result of differences in E, while G, within a given E, had a lesser effect. In addition to using the median value for $\%N_c$ (i.e., CNDC), the boundary values for the credible region (i.e., $CNDC_{lo}$ and $CNDC_{up}$) should be used in calculation of N nutrition index (and other calculations) to account for and propagate uncertainty. Additionally, this study found that the conventional statistical method used to derive CNDCs is subject to greater inferential bias resulting from biased experimental datasets (i.e., unbalanced distribution of N limiting and non-N limiting observations) than the Bayesian hierarchical method. Overall, this study provides additional evidence that $\%N_c$ is dependent upon G x E interactions; therefore, evaluation of crop N status or N use efficiency must account for variation in $\%N_c$ across G x E interactions.

4.1. INTRODUCTION

Identifying optimal crop nitrogen [N] status to maximize growth and yield production is an elusive goal. Traditionally, either the yield-goal approach or rate-response curves have been used to identify optimal N fertilizer application rate (Morris et al., 2018). The N nutrition index [NNI] is an alternative approach to the current paradigm and comprises a well-developed framework to determine optimal crop N status (Lemaire et al., 2019). Typically, NNI is used to determine crop N status using whole plant analysis and to direct adaptive N management within a growing season (Houlès et al., 2007; Morier et al., 2015). Unlike the yield-goal or rate-response approach where the optimal N fertilizer rate is empirically based on the marginal economic returns to yield from N fertilizer (i.e., economic optimum N rate [EONR]) under a given set of genotype [G], environment [E], and management [M] factors (Morris et al., 2018; Nigon et al., 2019), the NNI framework has conventionally been considered generalizable across E x M effects (e.g., year-to-year or geographic variability) and can be defined for any particular G effect (e.g., crop species or cultivar). In this manner, NNI is considered to represent intrinsic physiological properties (Sadras & Lemaire, 2014) rather than a parameter otherwise subject to variation under environmental conditions (e.g., net soil N supply) or management practices (i.e., rate, source, timing, and placement of N fertilizer).

The NNI approach is defined based on the allometric relationship of declining plant N concentration [$\%N_{Plant}$] with increasing plant biomass, referred to as the critical N dilution curve [CNDC], which defines the critical N concentration [$\%N_c$] below which relative growth rate is reduced (Gastal et al., 2015):

$$\%N_c = a\ W^{-b} \quad [4\text{-}1]$$

where W represents dry weight plant biomass, and *a* and *b* are empirically fitted parameters. Parameter *a* is numerically equivalent to $\%N_c$ expressed in units of g N 100 g^{-1} when W is equal to 1 Mg ha^{-1}, and parameter *b* effectively represents the rate of decline in $\%N_c$ as W increases. Using the CNDC, NNI values are then calculated as ratio of $\%N_{Plant}$ and $\%N_c$:

$$NNI = \%N_{Plant} / \%N_c \quad [4\text{-}2]$$

When NNI is greater than 1.0, crop N status is said to be in excess, and crop growth is not limited by N, while when NNI is less than 1.0, crop N status is deficient, and crop growth is limited by N. At NNI equal to 1.0, crop N status is optimal (Lemaire & Gastal, 1997).

A robust theoretical framework has been developed to explain decline in N concentration as biomass increases, but the application of this theory is most commonly restricted to the vegetative period where only metabolic and structural tissues are present (Greenwood et al., 1990; Justes et al., 1994; Sadras & Lemaire, 2014). Dilution of N in vegetative tissue occurs in relationship to an increasing proportion of structural biomass, with low N concentration, relative to metabolic (i.e., photosynthetic) biomass, with high N concentration (Gastal et al., 2015; Lemaire & Gastal, 1997).

Multiple previous studies have extended and empirically validated the CNDC relationships beyond its typical applications to describe declining N concentration over the entire crop growth cycle, including periods of reproductive growth, by including consideration of storage tissues in addition to structural and metabolic tissues (Duchenne et al., 1997;

Greenwood et al., 1986; Herrmann & Taube, 2004; Plénet & Lemaire, 2000). Dilution of N beyond the vegetative period primarily occurs as low N biomass (i.e., starch) accumulates in storage tissues such as grain or tubers, and the rate of decline is determined by the relative N concentration in storage biomass compared to vegetative biomass (Duchenne et al., 1997; Plénet & Lemaire, 2000). Duchenne et al. (1997) observed that as an increasing proportion of biomass accumulates in tubers, the rate of decline in N concentration increases with increasing biomass. Certain crops, such as potato, exclusively use a CNDC based on whole plant biomass due to the complex relationship between vine growth and tuber production (Bélanger et al., 2001a; Ben Abdallah et al., 2016; Duchenne et al., 1997; Giletto & Echeverría, 2015). Despite the validity of this approach, interpretating variation in CNDC observed between cultivars and geographies has been challenging.

However, recent work by Giletto et al. (2020) identified a mechanistic relationship underpinning the observed empirical relationships in N dilution for potato. The CNDC based on whole plant biomass reflects dilution in both the tuber and vine biomass, individually, and the increasing proportion of biomass allocated to low concentrations of N in biomass (i.e., tubers) as whole plant biomass increases. Giletto et al. (2020) also observed that varieties and locations with a greater proportion of biomass allocated to tubers have a greater value for parameter *b* of the CNDC, where parameter *b* of the CNDC represents the relative rate of decline in $\%N_c$ as biomass increases.

Based on this framework developed by Giletto et al. (2020), it is reasonable to expect that variation in CNDC across E and G would occur due to known variation in total biomass and harvest index (i.e., relative partitioning of biomass to tubers) across these G x E gradients. Understanding the effects of G x E interactions on crop N requirements and status is critical to improving agronomic outcomes and N use efficiency [NUE] within cropping systems (Lemaire & Ciampitti, 2020).

Previous development of CNDCs for potato (Bélanger et al., 2001a; Ben Abdallah et al., 2016; Duchenne et al., 1997; Giletto & Echeverría, 2015) has been conducted using a non-uniform set of statistical methods and with limited quantification of uncertainty in either the range of plausible $\%N_c$ values or the fitted parameter values themselves. This makes it difficult to ascertain whether observed differences in CNDCs result from underlying G x E effects or are confounded by the limitations of the statistical approach.

The conventional approach to fit a CNDC, consists of a two-step process: first, the critical points from the relationship of $\%N_{Plant}$ as a function of biomass are selected using statistical criteria; second, a negative exponential curve is fit to the subset of critical points using non-linear regression. There are two commonly used statistical approaches to identify critical points: (1) linear-plateau curve fit and (2) ANOVA and protected multiple comparison.

Using a linear-plateau curve to derive critical points was originally suggested by Justes et al. (1994). This approach is rigorous and requires sufficient empirical data such that a linear-plateau curve can be identified (i.e., at least one N limiting and at least two non-N limiting data points) for each observation date. Therefore, this approach can be difficult or impossible to implement due to potential limitations of the experimental data used such as insufficient levels of N treatments (i.e., fewer than three treatment levels) or interactions between management practices and environmental conditions (i.e., all observations are either N limiting or non-N limiting).

In contrast, many studies use methods similar to Ben Abdallah et al. (2016) where critical points are determined using a simplified statistical method. In this approach, ANOVA is first used to identify experimental dates where variation in biomass is statistically significant. Subsequently, a protected multiple comparisons analysis is used to identify which experimental treatments had the highest level of biomass – the treatment level with the significantly greatest level of biomass is then defined as the critical point. While this statistical method is more flexible to implement, it cannot resolve deficiencies in the underlying empirical data (i.e., insufficient level of N treatments, interactions with environmental conditions) that the linear-plateau method was designed to discriminate against. Therefore, the critical points selected using the simplified method may be biased when implemented using biased empirical data (e.g., without sufficient quantity of both N limiting and non-N limiting observations).

New statistical methods developed first by Makowski et al. (2020) provide a framework which allows for standardization in statistical approach, quantification of uncertainty, and a means to directly evaluate differences in CNDCs for various G x E interactions. In short, this novel framework implements a hierarchical Bayesian model which simultaneously identifies critical points using the linear-plateau method (e.g., Justes et al. (1994)) while fitting the negative exponential curve which defines $\%N_c$. The advantage of this method is that it fits the CNDC from the entire set of experimental data and removes the arbitrary intermediate step of separately identifying critical points. While this approach is newly developed, it has already been used by Ciampitti et al. (2021) and Yao et al. (2021) to evaluate differences in CNDCs across G x E interactions for maize and wheat cropping systems, respectively. Through a single-step process, the Bayesian hierarchical method both eliminates the need to separately identify critical points and implements the theoretically preferred method (e.g., linear plateau curve) to select critical points.

Building upon the previous work, the objectives of this study are to 1) develop CNDCs using the hierarchical Bayesian framework for potato varieties in Minnesota (from both previously published and unpublished experimental data) and for potato varieties in Argentina (Giletto & Echeverría, 2015), Canada (Bélanger et al., 2001a), and Belgium (Ben Abdallah et al., 2016) (from previously published experimental data), 2) extend the implementation of the hierarchical Bayesian framework to compare CNDCs across G x E interactions (i.e., variety, location) based on the uncertainty in $\%N_c$ and curve parameters *a* and *b*, 3) identify the optimal methods to determine uncertainty in $\%N_c$ for use in calculating NNI and other derivative metrics, and 4) compare CNDCs developed with the hierarchical Bayesian framework methods to previously published CNDCs for the same data with different statistical methods.

4.2. MATERIALS AND METHODS

4.2.1. EXPERIMENTAL DATA

This study combines experimental data from both newly reported and previously published sources (Ben Abdallah et al., 2016; Giletto et al., 2020). The data used for analysis in this study are summarized in Table 4-1 and the relevant methods related to the experimental trials are reported below. All individual experimental observations used in this study are presented in the Supplemental Materials (Table 4-S1).

4.2.1.1. Newly Reported Data – Minnesota

Six individual plot-scale field experiments were conducted over a total of eight years (MN-1: 1991–1992; MN-2: 2014-2015, MN-3: 2016, MN-4: 2018-2019, MN-5: 2019, MN-6: 2020) on irrigated plots at the Sand Plain Research Farm [SPRF] in Becker, MN (45º 23' N, 93º 53' W) (Table 4-2). Mean temperature at this station is 7.1 ºC and mean annual precipitation is 809 mm for the 30-year period from 1981 to 2010 (Arguez et al., 2010). The soil at this station is characterized as a Hubbard loamy sand (Sandy, mixed, frigid Entic Hapludolls) and excessively well drained with low available water holding capacity (Hansen & Giencke, 1988; USDA NRCS, 2013). Apart from experimental N and variety treatments, all management and cultural practices were managed by the staff at the SPRF in accordance with common practices for the region (Egel, 2017), nutrients were applied based on soil samples and University recommendations (Franzen et al., 2018; Rosen, 2018), and supplemental irrigation was applied based on the University recommended checkbook method (Steele et al., 2010; Wright, 2002). Additional details on experimental procedures for these studies have been previously reported (Table 4-2).

A randomized complete block design with three or four replicates was used in each field experiment. All studies evaluated at least 3 nitrogen rates (0 – 400 kg N ha^{-1}) for Russet Burbank potato [*Solanum tuberosum* (L.)], with some studies evaluating additional potato varieties (Table 4-2). Those studies that evaluated multiple varieties had either a factorial design, or split-plot design with variety treatment as the whole-plot and nitrogen treatment as the split-plot. Plots in these studies were between 5.4 – 6.4 m wide (6 or 7 x 0.9 m rows) and 6.1 – 9.1 m long. Planting density ranged between 36,000 – 48,000 plants ha^{-1}, depending on year and variety. Experiments were planted each year in late-April to early-

May and were mechanically harvested in mid-September with vines terminated one to two weeks prior to harvest. A summary of N management practices and varieties evaluated for each of these studies is given below (Table 4-3).

Samples of vine biomass were harvested immediately prior to mechanical termination for determination of fresh weight vine yield. Harvested tubers were mechanically sorted into weight classes and graded (USDA, 1997), and fresh weight tuber yield was determined as the sum of all weight classes and tuber grades. Harvested biomass was oven dried at 60^{o}C to determine dry matter content of vines and tubers. Dry weight tuber and vine biomass was calculated as the product of fresh weight and dry matter content for each tissue respectively. Total N concentration of vines and tubers was determined from subsamples of plant tissues with either combustion analysis (Elementar Vario EL III, Elementar Americas Inc., Mt. Laurel, NJ) using standard methods (Horneck & Miller, 1998), or with the salicylic Kjeldahl method (Horwitz et al., 1970). Total N content of vines and tubers was calculated as the product of N concentration and dry weight biomass for each tissue respectively. Total plant N content [N_{Plant}] (kg N ha^{-1}) was calculated from the sum of tuber and vine N content. Total plant dry weight biomass [W] (Mg dry wt. ha^{-1}) was calculated from the sum of vine and tuber dry weight biomass. Plant N concentration [$\%N_{Plant}$] (g N 100 g^{-1}) was calculated as the ratio of N_{Plant} to W.

Whole-plant samples were also regularly collected during the period of late-May to early-September (Table 4-4). Two to three plants were harvested from each plot on four to six dates each year with vines, roots, and tubers each measured separately. Dry weight biomass, N concentration, and N content for vines and tubers were determined for these in-season plant tissue samples using the methods described above. Calculations for W, N_{Plant}, and $\%N_{Plant}$ were the same as methods previously described above.

4.2.1.2. Previously Published Data – Belgium, Argentina, and Canada

Experimental data reported in two previous studies, Giletto et al. (2020) and Ben Abdallah et al. (2016), were included in the analysis conducted for the present study. The data from Giletto et al. (2020) comprises two separate experimental data sets from Argentina (Giletto & Echeverría, 2015) and Canada (Bélanger et al., 2000, 2001a, 2001b). All data from the Giletto et al. (2020) study used in the present analysis was included in this previous publication.

In the Canadian study, two varieties (Russet Burbank and Shepody) and four N fertilization rates (0, 50, 100, and 250 kg ha^{-1}) were evaluated under irrigated and non-water limiting conditions with each variety having four site-years of experimental data and 10 sampling dates per site year (Table 4-1). These experiments were conducted in the upper St. John River Valley of New Brunswick. The soil texture for these experiments was classified as either loam or clay loam with organic matter content ranging from 2.6 to 3.0%. During the period from May to October, the average temperature ranged from 14 to 19 °C while the cumulative rainfall ranged from 186 to 243mm.

In the Argentina study, five varieties (Bannock Russet, Gem Russet, Innovator, Markies Russet, and Umatilla Russet) and four N fertilization rate (0, 80, 150, 250 kg N ha^{-1}) were each evaluated under irrigated and non-water limiting conditions for between two and four site-years with between four and five sampling dates per site year (Table 4-1). These experiments were conducted in Balcarce in the province of Buenos Aires. The soil texture for these experiments was classified as loam with organic matter content ranging from 4.2 to 5.2%. During the period from October to March, the average temperature ranged from 17 to 19°C, the cumulative rainfall ranged from 385 to 587mm.

The data from Ben Abdallah et al. (2016) represents multiple experimental data set from Belgium. Only a portion of the data from the Ben Abdallah et al. (2016) study used in the present analysis was included in this previous publication – while the dry weight biomass data were previously reported, the nitrogen concentration data from the Ben Abdallah et al. (2016) experiment is reported for the first time in this work.

In the Belgium studies, three to six N rates (ranging from 0 to 250 kg N ha-1) were evaluated for two varieties (Bintje and Charlotte) for 17 and 7 site-years, respectively, with between one and eight sampling dates per site year (Table 4-1). These experiments were conducted in various regions across Belgium. The soil texture for these experiments was classified as loam, sandy loam, silt loam, or silty clay loam with organic matter content ranging from 1.3 to 2.6%. During the period from April to August, the cumulative rainfall ranged from 289 to 458mm.

4.2.2. Statistical Methods

Based on the general approach outlined by Makowski et al. (2020), this study implemented a Bayesian hierarchical framework to infer CNDC parameters for each location and variety within location, assess the uncertainty in model parameters and $\%N_c$, and compare fitted CNDCs across the effects of location and variety.

In summary, this statistical approach uses the entire set of experimental data (Figure 4-1a) and does not require any preliminary or intermediary statistical analysis. At the level of each experimental sampling date, a linear-plateau curve is fit for biomass as a function of N concentration (Figure 4-1b) and the join point of the linear-plateau curve is used to define the $\%N_c$. Simultaneously, a negative exponential curve (i.e., CNDC) is fit across all experimental sampling dates for a given effect level of the hierarchical model (e.g., location, variety) where the critical point of each linear-plateau curve lies exactly upon the negative exponential curve (Figure 4-1b). In this manner, the linear-plateau curve fitted for any given date is influenced by the data from all other experimental sampling dates through the fitting of the negative exponential curve. In comparison, the conventional statistical approach fits a negative exponential curve to the subset of critical points (Figure 4-1c) which are identified via an intermediate statistical analysis (i.e., ANOVA and protected multiple comparisons).

The Bayesian hierarchical framework outlined by Makowski et al. (2020) was extended to explicitly include E and G interactions within the fitted model. This was implemented through the nesting of experimental data according to location and variety within location and the linear-plateau curve fitted for each experimental sampling date can be pooled at various nested levels of location or variety within location (Figure 4-2).

Using *R* (R Core Team, 2021a), the *brms* package (Bürkner, 2017, 2018) was used to implement the statistical framework outlined by Makowski et al. (2020). The *brms* package, an interface to *Stan* (Carpenter et al., 2017), was chosen due to the ability to include group-level (i.e., random effects) which allows for the fit of a single model for all of the experimental data and improves model performance through the inclusion of partial pooling (i.e., data from all other levels of an effect influence the inference for a particular level) (McElreath, 2020). The *brms* package includes a user-friendly modeling language, robust documentation, and a diverse set of tools to analyze and assess models.

A non-linear *brms* model was defined by combining the two separate expressions used by Makowski et al. (2020) to parameterize the Bayesian hierarchical model as previously implemented with *rjags* (Plummer, 2019) and *JAGS* statistical software (Plummer, 2013).

The first expression from Makowski et al. (2020) represents the linear-plateau component:

$$\mathrm{W} = min(W_{Max,\mathrm{i}} + S_{\mathrm{i}} \cdot (\%\mathrm{N}_{\mathrm{Plant}} - \%\mathrm{N}_{\mathrm{c}}), W_{Max,\mathrm{i}}) \qquad [4\text{-}3]$$

where S_{i} and $W_{Max,\mathrm{i}}$ are the slope of the linear-plateau curve and the maximum value of biomass (i.e., plateau) for a given date [i], respectively, *min* represents the minima function (i.e., the plateau component), and W, $\%\mathrm{N}_{\mathrm{Plant}}$, and $\%\mathrm{N}_{\mathrm{c}}$ have the same meaning as previously defined in this present study. This linear-plateau curve is defined with N concentration as the independent variable and biomass as the dependent variable and is written in point-slope form where the reference point used is the critical point.

The second expression from Makowski et al. (2020) represents the CNDC component:

$$\%\mathrm{N}_{\mathrm{c}} = a\, W_{Max,\mathrm{i}}^{-b} \qquad [4\text{-}4]$$

where a and b are the parameters that define the negative exponential curve and $\%\mathrm{N}_{\mathrm{c}}$ and $W_{Max,\mathrm{i}}$ have the same meanings as defined above.

Using algebraic substitution (i.e., for $\%\mathrm{N}_{\mathrm{c}}$), these two expressions (Eq. [4-3] and Eq. [4-4]) were combined to produce following non-linear *brms* model formula:

$$W \sim min(W_{Max,\mathrm{i}} + S_{\mathrm{i}}\ (\%\mathrm{N}_{\mathrm{Plant}} - (a\ W_{Max,\mathrm{i}}^{\ -b})),\ W_{Max,\mathrm{i}}) \qquad [4\text{-}5]$$

Two group-level (i.e., random) effects were specified for this *brms* model to parameterize the nested structure (Figure 4-2). First, the parameters S and W_{Max} included group-level effects to fit a linear-plateau curve to each experimental sampling date:

$$W_{Max} + S \sim 1 + (1 \mid index) \qquad [4\text{-}6]$$

where *index* represents the unique level of each experimental sampling date, nested within a given level of variety within location. Second, the parameters a and b included group-level effects to fit the CNDC:

$$a + b \sim 1 + (1 \mid location) + (1 \mid location{:}variety) \qquad [4\text{-}7]$$

where *location* and *location:variety* represents the unique effect level for location and variety within location, respectively.

The *brms* model was fitted using 4 chains and 10000 iterations with 3000 warmups per chain. The priors for this model were chosen based on expert knowledge (i.e., previously reported values), empirical observations (i.e., summary values from the data set), and the joint prior predictive distribution (i.e., if a set of relatively uninformative priors led to biologically or physically impossible predictions, the prior ranges were narrowed) (Schad et al., 2021). This is particularly important for hyperparameters dealing with the standard deviation between groups in a hierarchical model. A summary of the prior values used in this model is given below (Table 4-5).

The entire workflow used to generate this analysis is reproducible and available via GitHub repository (https://github.com/bohm0072/cndc_bayesian_eval). The *renv* package (Ushey, 2021) was used to document the computing environment utilized while conducting this analysis to ensure code portability and reproducibility.

4.2.3. EVALUATING UNCERTAINTY

4.2.3.1. Critical N Dilution Curve Parameter Uncertainty

After the statistical model was successfully fit to the data (n=28,000 draws), values for parameters *a* and *b* of the CNDC were reported at the 0.05, 0.50 (i.e., median) and 0.95 quantiles for the effect levels of *location* and *location:variety* to determine the 90% credible interval for each parameter. The correlation between values for parameters *a* and *b* was determined for each effect level of *location:variety* using the fitted parameter values at the level of the individual draws.

4.2.3.2 Critical N Concentration Uncertainty

The $\%N_c$ for a set of discrete values of W between 1 Mg ha^{-1} and the maximum observed value of W in the experimental data set was calculated for each individual draw based on the fitted values of parameters *a* and *b* for that draw. From the distribution of $\%N_c$ values, the 0.05, 0.50 (i.e., median) and 0.95 quantile values were identified for each effect level of *location:variety* to determine the 90% credible region for $\%N_c$. This approach makes maximal use of the jointly estimated parameters contained in the posterior distribution.

To develop curves approximating the upper and lower boundaries of the 90% credible region for $\%N_c$ (i.e., the 0.05 and 0.95 quantile values, respectively), a negative exponential curve of the same form as the CNDC (i.e., $y = a\,x^{-b}$) was fit using *nls* (R Core Team, 2021b) to the set of data previously identified as defining the boundaries of the 90% credible region (i.e., 0.05 and 0.95 quantile values). These curves approximating the upper and lower boundaries of the credible region are respectively referred to as $CNDC_{up}$ and $CNDC_{lo}$, where parameters a_{up} and b_{up} correspond to $CNDC_{up}$ and parameters a_{lo} and b_{lo} correspond to $CNDC_{lo}$.

Additionally, an estimate of the 90% credible region was calculated by using the boundary values of the 90% credible interval of parameters *a* and *b*. The estimate for the upper boundary of the credible region for $\%N_c$ was determined from the 0.95 quantile value for parameter *a* and 0.05 quantile value for parameter *b*; the estimate for the lower boundary of the credible region of $\%N_c$ was determined from the 0.05 quantile value for parameter *a* and 0.95 quantile value for parameter *b*. This approach does not account for the joint estimation of parameters offered by the Bayesian approach; therefore, the paired combination for parameters *a* and *b* (i.e., 0.05 and 0.95 quantiles) might not actually occur in the posterior distribution.

To compare the various methods described above, the difference in critical N concentration [$\Delta\%N_c$] was calculated between the 0.50 quantile (i.e., median) value for $\%N_c$, designated as the reference values (i.e., $\Delta\%N_c$ with constant value of zero), and the various methods to quantify uncertainty (i.e., 90% credible region for $\%N_c$, $CNDC_{up}$ & $CNDC_{lo}$, and estimates of credible region for $\%N_c$ using 90% credible interval for parameters *a* and *b*). In this manner, the $\Delta\%N_c$ for each method to quantify uncertainty in $\%N_c$ can be directly compared.

4.2.3.3. Comparing Critical N Concentration across G x E Effects

Similar to the above methods, the $\%N_c$ for each draw was calculated across a set of discrete values of W over the range of 1 Mg ha^{-1} and the maximum observed value of W in the experimental data set. At the effect level of *location:variety*, the difference between the $\%N_c$ for a given comparison and reference CNDC (i.e., $\Delta\%N_c$) was calculated at each value of W. From this computed set of $\Delta\%N_c$, the 0.05, 0.50 (i.e., median) and 0.95 quantile values were identified for each effect level of *location:variety* to determine the 90% credible region for $\Delta\%N_c$. For a given range of W values, the comparison curve considered to be not significantly different from the reference curve if the $\Delta\%N_c$ values for the 0.05 and 0.95 quantile values of $\%N_c$ were respectively less than and greater than zero (i.e., the 90% credible region for $\Delta\%N_c$ contains zero). In the case where the 0.05 quantile value for $\Delta\%N_c$ was greater than zero, the comparison curve was considered to have a significantly greater $\%N_c$ than the reference curve. In the case where the 0.95 quantile value for $\Delta\%N_c$ was less than zero, the comparison curve was considered to have a significantly lower $\%N_c$ than the reference curve. To evaluate $\Delta\%N_c$ in the present study, the $\%N_c$ for a given effect level of *location:variety* was compared to all other levels, and this approach allows for the direct evaluation of $\Delta\%N_c$ across G x E effects.

4.2.3.4. Comparing Critical N Concentration across Statistical Methods

An analogous method was also used to compare the CNDCs fitted in the present study to the CNDCs published in previous studies (i.e., Ben Abdallah et al. (2016); Giletto et al. (2020)). Specifically, the previously published curves were evaluated to see if they fell within the 90% credible region for the corresponding curve fitted with the hierarchical

Bayesian method in the present study. Using the determined credible region for $\%N_c$, it is possible to identify the range for which two CNDCs are significantly different. If the previously identified $\%N_c$ value falls outside of the credible region for $\%N_c$ identified in this study, then the two curves are determined to be significantly different over the range for which the previous value falls outside of the credible region. This approach allows for direct evaluation of differences in $\%N_c$ for CNDCs developed from the same set of data across various statistical methods.

4.3. RESULTS

4.3.1. FITTED CRITICAL N DILUTION CURVE

The posterior distribution of fitted values for CNDC parameters *a* and *b* are presented below (Figure 4-3) showing the median value and 90% credible interval (i.e., 0.05 and 0.95 quantile values). For parameter *a*, there was no significant difference for the effect of location at 90% credible interval threshold (Figure 4-3a). Although Argentina has a numerically greater value of parameter *a* (4.95) than the other three locations (4.74 – 4.77), these differences are not significant. Additionally, the variation in parameter *a* for the variety within location effect is negligible and not statistically significant (Figure 4-3a).

For parameter *b*, there were significant differences for both the effect of location and variety within location at a 90% credible interval threshold (Figure 4-3b). For location, Argentina had the lowest value for parameter *b* (0.175), while Canada had a greater value for parameter *b* (0.448) than Argentina but lower than either Belgium (0.561) or Minnesota (0.582). The difference between parameter *b* for Belgium and Minnesota was not significant. For the variety within location effect, parameter *b* significantly varied for varieties in Argentina and Canada, while there were no significant differences in parameter b within either Belgium or Minnesota. For Argentina, Innovator had the greatest value for parameter b (0.212), followed by Gem Russet, Umatilla Russet, Markies Russet, and Bannock Russet (0.178, 0.165, 0.155, and 0.140, respectively). The difference between Innovator and Umatilla Russet, Markies Russet, and Bannock Russet was significant, while all other differences between varieties were not significant. For Canada, Russet Burbank had a significantly higher value for parameter *b* (0.489) than Shepody (0.412).

There was a positive correlation found between parameter *a* and *b* (Figure 4-4) which indicates that quantifying differences in these parameter values independently (Figure 4-3) is not appropriate to describe the uncertainty in $\%N_c$ determined by the correlated parameters. Stated alternatively, significant differences for either parameter *a* or *b* do not necessarily imply that differences in $\%N_c$ are also significant.

Critical N dilution curves for each variety within location and the experimental data, median linear-plateau curve for each experimental sampling date, and median value of $\%N_c$ are presented (Figure 4-5). The individual linear-plateau curves fitted for each experimental sampling date nested within each level of the variety within location effect are presented in the Supplemental Materials (Figure 4-S1).

For the Argentina varieties, more than 60% of the observed data fall below the CNDC (i.e., represent N limiting conditions) with over 40% of sampling dates having exclusively N limiting conditions observed. For both the Belgium and Minnesota varieties, more than 80% of the observed data fall above the CNDC (i.e., represent non-N limiting conditions) with almost 30% of sampling dates having exclusively non-N limiting conditions observed. For the Canada varieties, over 60% of observed data represented non-N limiting conditions but less than 10% of sampling dates had exclusively non-N limiting conditions observed.

4.3.2. Critical N Concentration Uncertainty

The credible region for $\%N_c$ varies across variety within location and across levels of biomass (Figure 4-6). The symmetry of the credible region distribution varies by variety within location. Some levels of variety within location, such as Argentina x Gem Russet, have a skewed distribution, while other levels, such as Canada x Shepody, have a symmetrical distribution (Figure 4-6a). There are also differences in the range of the credible region, where some varieties within location, such as Argentina x Umatilla Russet, have greater uncertainty in $\%N_c$ than others, such as Minnesota x Russet Burbank. The uncertainty in $\%N_c$ also varies across the level of biomass for a given CNDC. For example, as the level of biomass increases, Argentina x Umatilla Russet has an increasing credible region range, Minnesota x Russet Burbank has a decreasing credible region range, and Argentina x Bannock Russet has a nearly constant credible region range.

Estimation of the upper and lower boundaries of the 90% credible region using the non-linear regression method (i.e., $CNDC_{lo}$ and $CNDC_{up}$) (Table 4-6) appears to be reasonable based on graphical evaluation (Figure 4-6). However, these fitted $CNDC_{lo}$ and $CNDC_{up}$ curves do not themselves represent a draw directly from the posterior distribution and do not necessarily represent the most extreme possible curves (e.g., it is plausible to have an individual draw that goes from the lower left to upper right corner of the interval, or vice versa) (Figure 4-6b). While credible regions with boundaries that are non-monotonic (e.g., Argentina x Innovator) have portions of the curve fit approximation that are poorer performing, the credible regions with monotonic boundaries (e.g., Minnesota x Dakota Russet) seem to be satisfactory across the entire range of the curve.

However, the approximation of uncertainty in $\%N_c$ based directly on uncertainty in CNDC parameters *a* and *b*, using the previously determined credible interval boundaries (Figure 4-3), were found to contain the entire credible region for all varieties within location evaluated (Figure 4-6a). Therefore, this approach directly using the uncertainty in CNDC parameters is quite uninformative and should be used as a last resort to estimate $\%N_c$ uncertainty when the credible region defined from either the original model fit or from the paired $CNDC_{lo}$ or $CNDC_{up}$ curves is unavailable. In the absence of the credible region defined directly from the fitted hierarchical Bayesian model, the $CNDC_{lo}$ and $CNDC_{up}$ (Table 4-6) are a suitable first-order representation of the credible region for $\%N_c$.

4.3.3. Evaluating Differences between Critical N Concentration

4.3.3.1. Differences Related to Genotype x Environment Effects

While an evaluation of the pairwise differences between all varieties within location was conducted and is presented in the Supplemental Materials (Figure 4-S2), a subset of the results comparing Minnesota x Russet Burbank to all other varieties within location presented in detail here (Figure 4-7).

For Minnesota x Russet Burbank, there were no significant differences in $\%N_c$ for any level of W evaluated with any of the other varieties in Minnesota (i.e., Clearwater, Dakota Russet, Easton, and Umatilla Russet) or with the Belgium varieties (i.e., Bintje, and

Charlotte). The $\%N_c$ for both of the Canadian varieties (i.e., Russet Burbank, and Shepody) were significantly greater than that for Minnesota x Russet Burbank when biomass values were greater than 2 Mg ha^{-1}. The $\%N_c$ for Canada x Russet Burbank and Canada x Shepody were up to 0.3 and 0.6 g N $100g^{-1}$ greater than that for Minnesota x Russet Burbank, respectively. The $\%N_c$ for the Argentina varieties (i.e., Bannock Russet, Gem Russet, Innovator, Markies Russet, and Umatilla Russet) were significantly greater than for Minnesota x Russet Burbank, except for at a biomass value of 1.0 Mg ha^{-1}, with a difference in value depending on variety of up to 2.4 g N 100 g^{-1}.

There are two notable findings to point out. First, there were no significant differences between Minnesota x Russet Burbank and any other varieties evaluated in Minnesota (i.e., when controlling for E, no significant differences due to G). This finding did not hold for all varieties within location evaluated, however; while there was no significant difference between the varieties evaluated in Belgium, there were significant differences between the varieties evaluated in Canada and some of the varieties evaluated in Argentina (Figure 4-S2). Second, the comparison between the Minnesota x Russet Burbank and Canada x Russet Burbank curves as well as the comparison between the Minnesota x Umatilla Russet and Argentina x Umatilla (Figure 4-S2) were both significantly different (i.e., when controlling for G, a significant difference due to E).

Taken together, these findings provide evidence that the effect of E, even when controlling for G, can result in significantly different $\%N_c$; additionally, this provides evidence that differences in G within a given E do not necessarily result in significant different $\%N_c$. Therefore, these findings suggest that E is relatively more important than G in determining $\%N_c$.

4.3.3.2. Differences Related to Statistical Methods

Comparing the curves fit in the present study with the Bayesian hierarchical method to the curves fit in the previous studies using conventional statistical methods, there were significant differences between statistical curve fit methods for all varieties within location evaluated (Figure 4-8). None of the previous CNDCs fall entirely within the credible region for the respective CNDCs developed in the present study.

The $\%N_c$ from the previously developed CNDCs for the Argentina varieties (Giletto & Echeverría, 2015) was significantly less than that from the present CNDCs across all varieties for biomass levels of greater 5 Mg ha^{-1} (Figure 4-8). The magnitude of this difference was relatively large, with the $\Delta\%N_c$ between the previous and present method ranging up to –0.6 to –1.1 g N 100 g^{-1}, depending on variety. Therefore, it appears that the statistical methods used by Giletto and Echeverría (2015) selected biased critical points due to a overrepresentation of N limiting observations in the experimental dataset leading to a systematic underestimation of the $\%N_c$.

The $\%N_c$ from the previously developed CNDCs for Belgium (Ben Abdallah et al., 2016) were significantly greater than that from the CNDCs developed in the present study (Figure 4-8). For all levels of biomass, $\Delta\%N_c$ between the previous and present methods was significantly different with a value of 0.7 g N 100 g^{-1}. Therefore, it appears that the statistical methods used by Ben Abdallah et al. (2016) selected biased critical points due to overrepresentation of non-N limiting observations in the experimental dataset leading to a systematic overestimation of the $\%N_c$.

The $\%N_c$ from the previously developed CNDCs for Canada (Bélanger et al., 2001a) was significantly greater for both Canada x Russet Burbank and Canada x Shepody than the present CNDCs for biomass levels of less than 3 Mg ha^{-1} and greater than 6 Mg ha^{-1}, respectively (Figure 4-8). Relative to the other locations, however, the CNDCs for Canada were the most similar between statistical methods, with small value for $\Delta\%N_c$ of only 0.2 g N 100 g^{-1}. Therefore, it appears that the statistical method used by Bélanger et al. (2001a) did not select biased critical points likely due to the minimal bias observed in this experimental dataset.

Because a CNDC using the conventional statistical methods has not been previously published for potato in Minnesota, no comparison across statistical methods is made for this experimental dataset. However, the bias observed in the Minnesota experimental dataset is similar to the bias found in the Belgium experimental dataset; therefore, using the conventional statistical methods to derive a CNDC for Minnesota would likely overestimate $\%N_c$ relative to the hierarchical Bayesian method.

4.4. DISCUSSION

4.4.1. IMPLICATION OF G X E VARIATION ON N USE EFFICIENCY

4.4.1.1. Critical N Utilization Efficiency

Understanding and properly interpreting the impact of G x E effects on NUE is a critical goal necessary to improve N fertilizer use; however, this must be done while controlling for the effect of crop N status (Lemaire & Ciampitti, 2020). The previous findings of Bohman et al. (2021) demonstrated that interpreting NUE and its constituent component of N utilization efficiency [NUtE] is directly related to the parameters of the CNDC through the critical N utilization efficiency curve [CNUtEC] which defines the critical value of NUtE [$NUtE_c$]:

$$NUtE_c = 1000\,(10\,a\,W^{-b})^{-1} \qquad [4\text{-}8]$$

where parameters a and b, and W have the same meaning and units as previously defined in the present study and $NUtE_c$ has units of g g^{-1} N. When NUtE is greater than $NUtE_c$, crop N status is deficient (i.e., NNI less than 1); conversely, when NUtE is less than $NUtE_c$, crop N status is excessive (i.e., NNI greater than 1).

The finding in the present study that the CNDC can vary across G x E effects and the finding from Bohman et al. (2021) of the intrinsic relationship between NUE and the CNDC together lead to the conclusion that the CNUtEC must also vary across the same G x E effects as the CNDC. Therefore, the effect of G x E on variation of $NUtE_c$ is one of the multiple set of factors that ultimately control NUE. Understanding and accounting for the G x E effect on the CNUtEC is therefore critically important to understand the impacts of G x E interactions on NUE. In other words, controlling for this G x E effect represents an additional requirement when evaluating and interpreting NUE above and beyond the previously known requirements of controlling for both NNI and biomass (Barraclough et al., 2010; Caviglia et al., 2014; Gastal et al., 2015; Lemaire & Ciampitti, 2020; Sadras & Lemaire, 2014).

4.4.1.2. Physiological Mechanisms

While the present study presents direct evidence of significant differences between CNDCs for potato across G x E effects, previous studies help describe the potential physiological mechanisms for this source of variation. The findings of Giletto et al. (2020) suggest that variation in CNDCs for potato across G x E effects is primarily due to differences in the relative rate of partitioning of biomass to tubers. For example, G x E effects that result in greater partitioning of biomass from vines (i.e., high N metabolic and structural tissue) to tubers (i.e., low N storage tissues) will result in greater N dilution (i.e., lower $\%N_c$) at the same level of total plant biomass.

Following from the above discussion of the CNUtEC and the findings of Giletto et al. (2020), G x E effects that increase the relative proportion of biomass partitioned to tubers will both decrease the $\%N_c$ and increase the $NUtE_c$ values. Therefore, future efforts to systematically improve NUE in potato through either management practices (M) (e.g., Bohman et al. (2021)) or crop breeding (e.g., Jones et al. (2021); Stefaniak et al. (2021); Tiwari et al. (2018)) should focus on identifying G x E x M interactions that result in an increased proportion of biomass partitioned to tubers.

Additionally, based on the larger magnitude of differences in $\%N_c$ between locations (i.e., E) compared to differences between varieties within a location (i.e., G) observed in this study (Figure 4-7, Figure 4-S2), it is reasonable to conclude that increases in NUE for potato resulting from decreasing $\%N_c$ will be of a greater magnitude from E rather than G effects.

4.4.1.3. Comparison to Other Crops

These findings contrasts somewhat with the previous studies evaluating G x E effects on $\%N_c$. Yao et al. (2021) found a similar magnitude of effect on $\%N_c$ for both G and E effects for wheat in China; however, Yao et al. (2021) also reported an E effect where $\%N_c$ for wheat in China was significantly difference from that reported by Makowski et al. (2020) for wheat in France. Ciampitti et al. (2021) found variation as a result of G x E interactions, but did not independently report either G or E effects. In any case, the magnitude of the difference in $\%N_c$ for any effect (i.e., G, E) or interaction (i.e., G x E) reported by the previous studies (Ciampitti et al., 2021; Makowski et al., 2020; Yao et al., 2021) is less than that observed for E in the present study.

Therefore, the impact of E on $\%N_c$ is not just significant for potato, but is also of much greater relative importance compared to other major crops (e.g., wheat, maize). This is because the magnitude of variability in $\%N_c$ due to G x E interactions is relatively greater for potato than other crops. In order to improve the understanding of this relationship between NUE and $\%N_c$, future work should continue to better characterize the relative partitioning of potato biomass to tubers across G x E effects.

4.4.2. Uncertainty in Critical N Concentration

4.4.2.1. Communicating Uncertainty in Critical N Concentration

This study as well as others that implemented Bayesian statistical methods to derive critical N dilution curves (Ciampitti et al., 2021; Makowski et al., 2020; Yao et al., 2021) clearly indicate that there is meaningful uncertainty in $\%N_c$ values. Therefore, the use of $\%N_c$ in subsequent calculations should include this inherent uncertainty. However, the direct use of the credible region defined from posterior distribution of the fitted Bayesian hierarchical model in subsequent calculations is impractical, and a method to concisely and accurately communicate the credible region remains necessary.

Our finding that the credible region can be satisfactorily estimated using an equation of the same form as the CNDC (Figure 4-6) suggests that an additional pair of negative exponential curves representing the upper and lower boundary of the credible region for $\%N_c$ (i.e., $CNDC_{lo}$ and $CNDC_{up}$) should be reported in future studies. In this manner, the median value and credible region for $\%N_c$ is defined by a set of three, two-parameter curves (i.e., CNDC – a, b; $CNDC_{up}$ – a_{up}, b_{up}; $CNDC_{lo}$ – a_{lo}, b_{lo}) which can be easily communicated and used in subsequent computations (Table 4-6).

4.4.2.2. Computing Uncertainty of Derived Parameters

Critical N concentration and the associated CNDC parameters are commonly used to derive and calculate other related parameters. For example, the calculation of NNI depends on both $\%N_{Plant}$ and $\%N_{c.}$ (Eq. [4-1] and Eq. [4-2]). However, to properly account for the uncertainty in $\%N_c$ when computing NNI, the upper [$\%N_{c,up}$] and lower [$\%N_{c,lo}$] bounds of the credible region should also be used to determine the upper [NNI_{up}] and lower [NNI_{lo}] bounds of NNI, where $\%N_{c,up}$ and $\%N_{c,lo}$ are calculated using the $CNDC_{up}$ and $CNDC_{lo}$, respectively:

$$NNI_{up} = \%N_{Plant} / \%N_{c,up} = \%N_{Plant} / (a_{up}\ W^{-b}{}_{up}) \quad [4\text{-}9]$$

$$NNI_{lo} = \%N_{Plant} / \%N_{c,lo} = \%N_{Plant} / (a_{lo}\ W^{-b}{}_{lo}) \quad [4\text{-}1]$$

This has important practical implications for interpreting NNI values. For example, in a case where NNI is less than 1 but NNI_{up} is greater than 1, it follows that crop N status would not be considered deficient (i.e., NNI is not significantly different from 1). In contrast, when both NNI and NNI_{lo} are greater than 1, it follows that crop N status would be considered surplus (i.e., NNI is significantly greater than 1). However, the threshold for considering significant differences in NNI will necessarily depend upon the threshold used for calculating $\%N_{c,lo}$ and $\%N_{c,up}$ (e.g., 90% confidence region). The conclusions of a small-plot trial evaluating the effect of various N fertilizer treatments and on yield and biomass (e.g., Bohman et al. (2021)) may draw different conclusions when uncertainty in calculated NNI values is explicitly considered.

Additionally, the parameters of the CNDC (i.e., a, b) are also used to parameterize other related curves such as the critical N uptake curve [CNUC] or the critical N utilization efficiency curve [CNUtEC] (Bohman et al., 2021). When computing the critical N uptake [N_c] or critical N utilization efficiency [$NUtE_c$] values defined by these curves, respectively, the parameters from the $CNDC_{lo}$ (i.e., a_{lo}, b_{lo}) and $CNDC_{up}$ (i.e., a_{up}, b_{up}) should be used to calculate the upper and lower bounds of these derived values. In general, any calculation depending on either $\%N_c$ or any equation that uses the parameters of the CNDC, should also additionally use the $CNDC_{lo}$ and $CNDC_{up}$ to account for uncertainty in $\%N_c$.

4.4.3. Evaluating Differences between Statistical Methods

While the occurrence of difference in CNDCs derived using the Bayesian hierarchical model compared to the conventional statistical methods (Figure 4-7) is itself notable, the magnitude of the differences found in the present study is especially remarkable. Because of its strong theoretical underpinning, $\%N_c$ and NNI are typically considered to be high fidelity measurements of crop N status, not affected by the subjectivity or relativity found in most other methods (Lemaire et al., 2019). However, the findings of the present study strongly suggest that this idealized conception of the NNI framework must be qualified within a particular application by the statistical methods used to derive the CNDC for a given experimental dataset.

Unfortunately, the direct evaluation of different statistical methods to calculate the CNDC from the same experimental dataset cannot directly answer the question of which statistical method or resulting CNDC is "correct" (i.e., most accurate, least biased). However, we can reasonably conclude from both deduction and from the findings of the present study that a Bayesian hierarchical model utilizing the linear-plateau method and leveraging partial pooling across effect levels will result in inference that is less subjected to potential bias in the experimental data set compared to the conventional statistical methods. Additionally, it extracts the greatest amount of information from a given dataset, as no data are excluded from the fitting of the total model.

Therefore, it appears preferable for the future development of CNDCs to utilize the Bayesian hierarchical method to both quantify uncertainty and reduce bias in $\%N_c$. Without addressing these limitations (i.e., bias and uncertainty), both directly resulting from the statistical methods used, the NNI framework cannot fulfill its core objective of providing an absolute reference of crop N status.

Additionally, with further development of adequate tools for this scientific computing task, the implementation of the Bayesian hierarchical framework for deriving the CNDC can be made trivial and may enable the development of CNDCs from existing but unutilized experimental datasets. Therefore, the development of a dedicated software library to implement the Bayesian hierarchical method is a priority for future research efforts.

4.5. CONCLUSIONS

First, this study demonstrated that there are significant differences between CNDCs developed across G x E effects for potato. Therefore, any application of $\%N_c$ must use an appropriate CNDC (i.e., not significantly different) for the G x E interaction being considered. Second, this study developed an approach to communicate uncertainty in $\%N_c$ through the concise set of six parameters defined by the CNDC (i.e., a, b), $CNDC_{lo}$ (i.e., a_{lo}, b_{lo}), and $CNDC_{up}$ (i.e., a_{up}, b_{up}), and the $\%N_c$ value computed from these three curves should be used in all subsequent computations to propagate uncertainty. Third, this study demonstrated that the statistical method used to derive CNDCs has an impact on the inferred $\%N_c$ values, and that the hierarchical Bayesian framework is less susceptible to bias due to biased experimental data than the conventional statistical methods. Therefore, future efforts to derive CNDCs should utilize the hierarchical Bayesian framework whenever possible. Fourth, the findings of this study suggest that variation in $\%N_c$ across G x E interactions necessarily extends to NUE, via the relationship between the CNDC and the CNUtEC. Therefore, NUE is dependent on the mechanisms that control N dilution (i.e., biomass partitioning), and future efforts to improve NUE should explicitly consider how G x E interactions affect N dilution.

4.6. References

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4.7. Figures

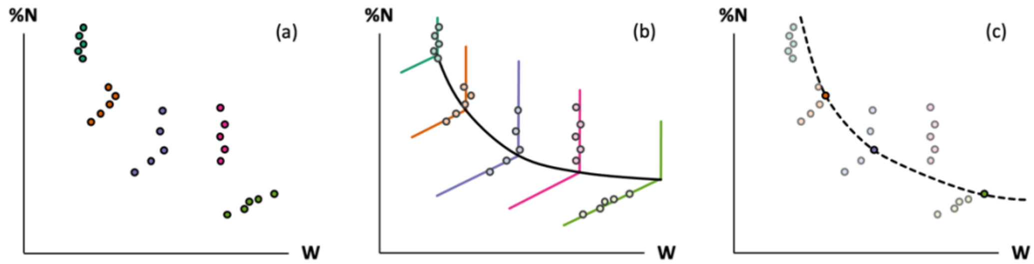


Figure 4-1. Hypothetical example comparing various statistical methods where plant N concentration [%N] as a function of biomass [W] on five experimental sampling dates for (a) raw experimental data, (b) linear-plateau curves (solid colored lines) fitted for each experimental sampling date (points within each date distinguished by color) and the critical N dilution curve (solid black line) fitted using the hierarchical Bayesian method based on Makowski et al. (2020), and (c) critical points (opaque) and non-critical points (transparent) selected using conventional statistical analysis (i.e., ANOVA and protected multiple comparison) with critical N dilution curve (dotted line) fitted using conventional methods (i.e., non-linear regression using only the critical points).

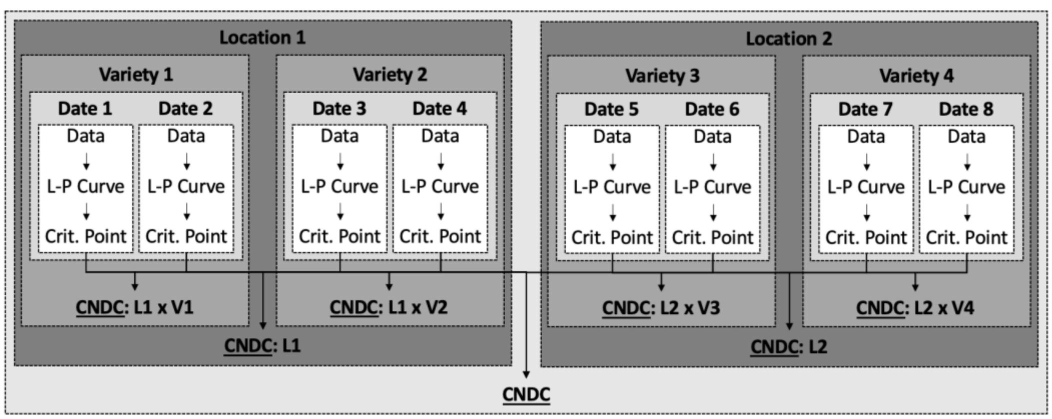
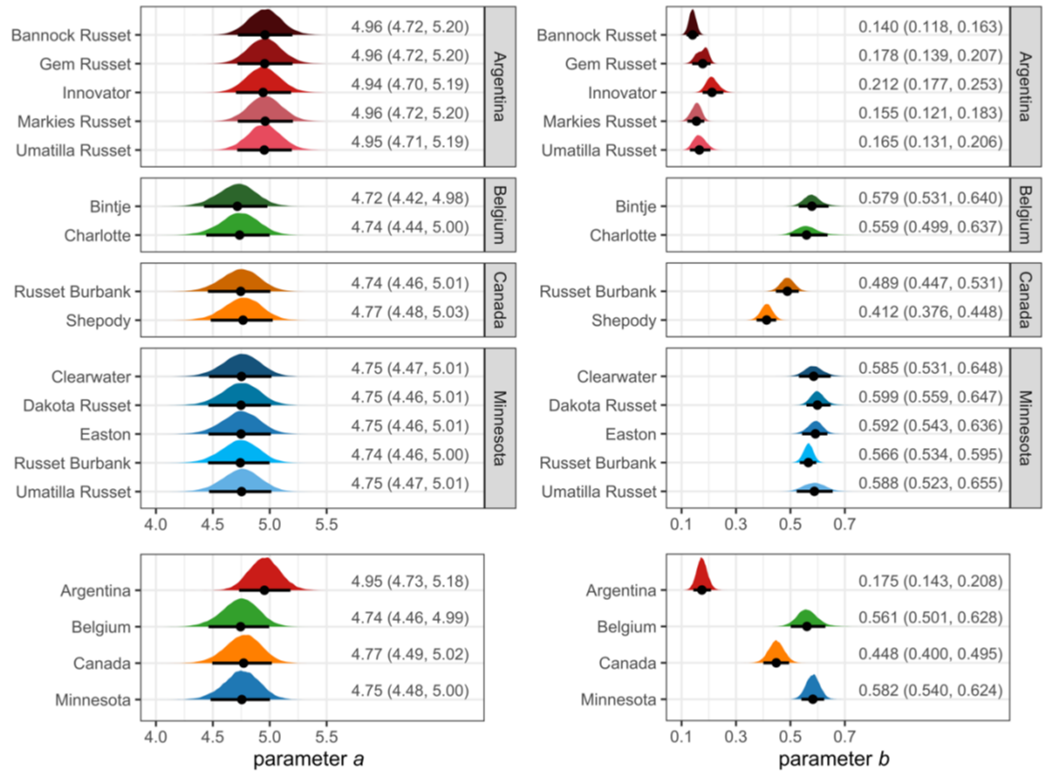


Figure 4-2. Flowchart showing nested structure used to fit critical N dilution curves [CNDC] using the hierarchical Bayesian method based on Makowski et al. (2020). Linear-plateau curves and critical points (i.e., the fitted join point of each linear-plateau curve) are identified at the level of each experimental sampling date and pooled at various levels of location and variety within location to determine the CNDC for that level. This hierarchical model structure simultaneously fits all individual levels of location and variety within location, as well as for the global level of all experimental data, which allows for direct comparison across levels.



(a) **(b)**

Figure 4-3. Posterior distribution of variety and variety within location effects for **(a)** parameter *a*; and **(b)** parameter *b*. Points represent median value and line represents 0.05 and 0.95 quantile range. Values displayed with the figures are the median value with the 90% credible interval boundaries (i.e., 0.05 and 0.95 quantiles) displayed within the parentheses.

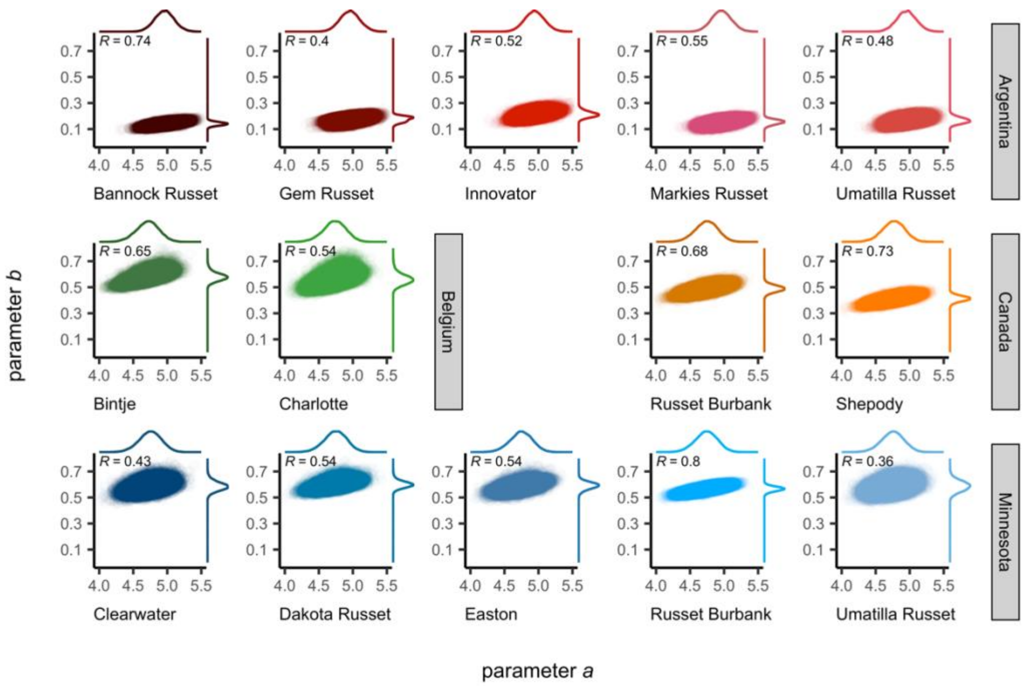


Figure 4-4. Distribution of posterior values for parameters *a* and *b* for each location within variety shown as a scatterplot with marginal density distribution given for each parameter. Pearson correlation coefficient [*R*] is displayed for the relationship between parameters *a* and *b*. Data are shown at the level of individual draws (n=28,000).

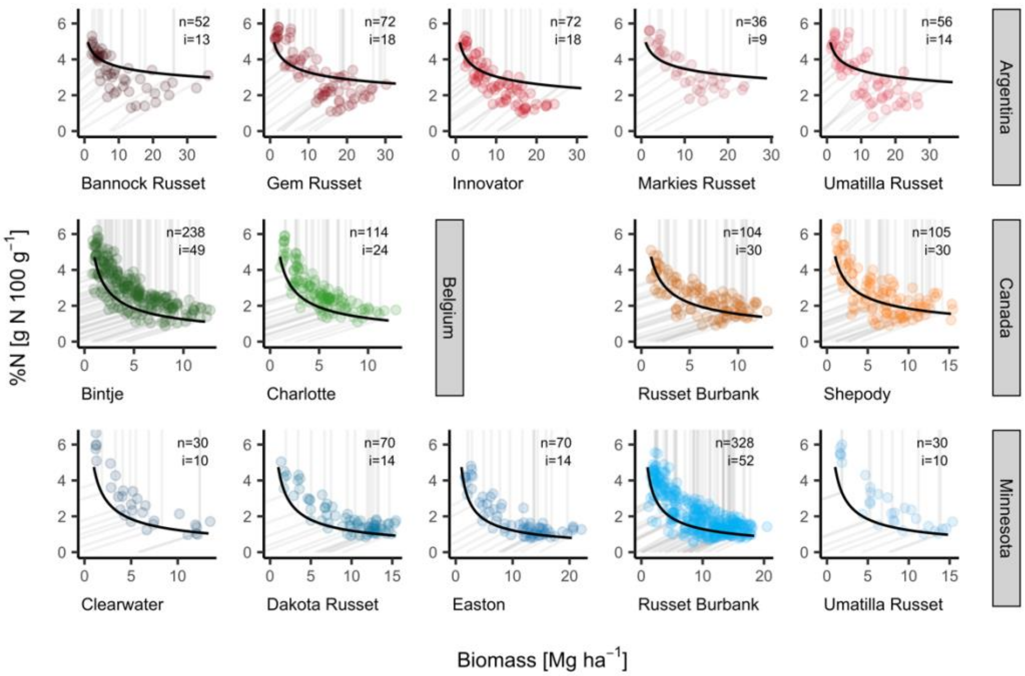


Figure 4-5. Critical N dilution curves (i.e., median value of critical N concentration [%Nc]) fitted from the hierarchical Bayesian model are shown as a solid black line for each location with variety. Biomass and nitrogen concentration [%N] data are displayed as points with the median linear-plateau curve for each sampling date shown as grey line. The number of samples [n] and the number of sampling dates [i] are displayed on each individual panel.

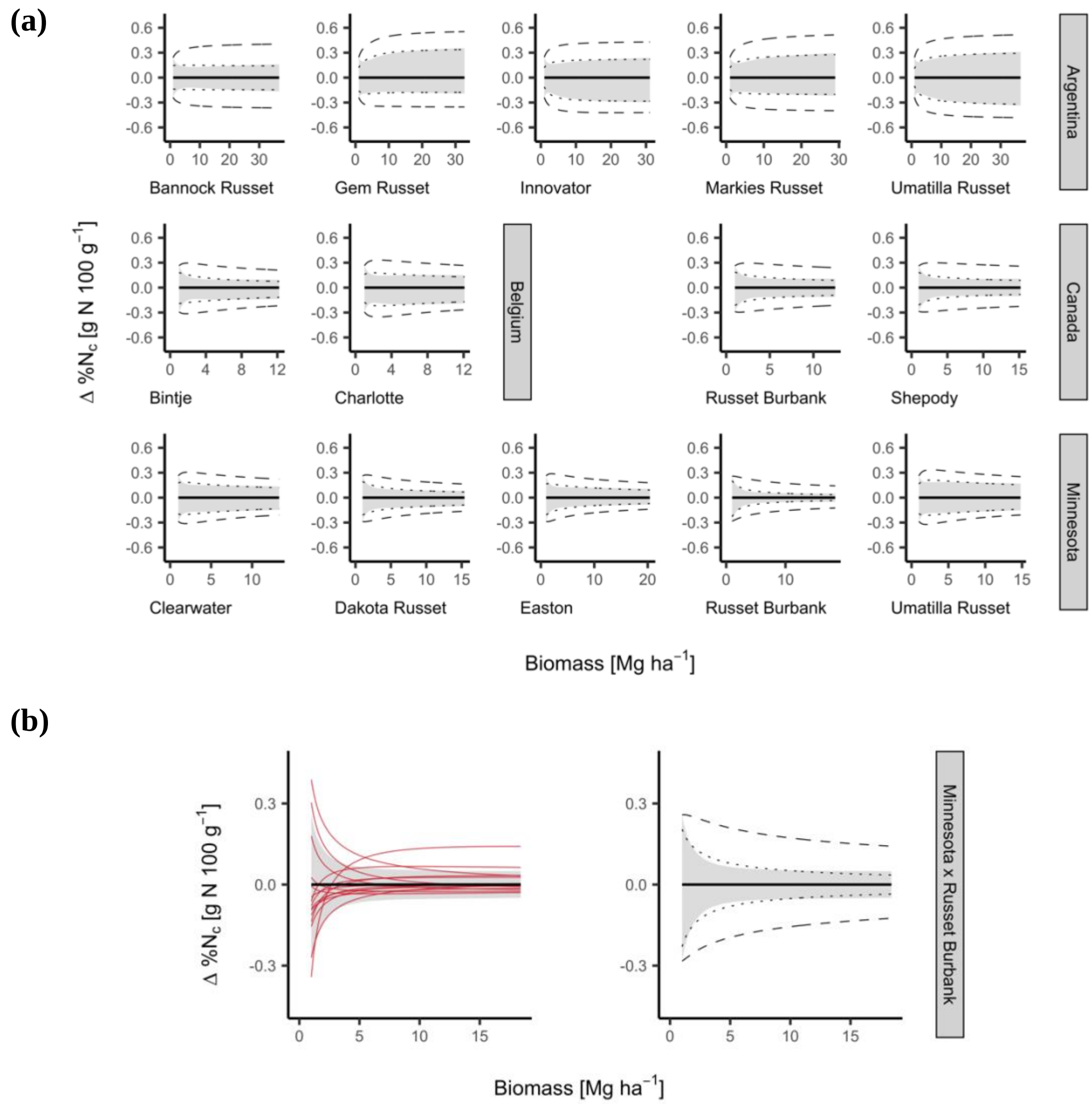


Figure 4-6. Comparison of the difference in critical N concentration values [Δ%N_c] between the median critical N concentration, represented as a solid black line at constant Δ%N_c value of zero, and the various methods to quantify uncertainty in critical N concentration [%N_c] where the magnitude of uncertainty in %N_c is equivalent the Δ%N_c value. The grey shaded region represents the 90% credible region (lower bound, 0.05 quantile; upper bound, 0.95 quantile) for the fitted Bayesian hierarchical model. The dotted lines represent an estimation of the upper and lower bound of the 90% credible region from using the non-linear regression method (i.e., $CNDC_{lo}$ and $CNDC_{up}$). The dashed lines represent an approximation of uncertainty in %N_c based on the posterior distribution of critical N dilution curve [CNDC] parameters *a* and *b*. Data are presented for **(a)** all levels of variety within location, and **(b)** shown in greater detail for Minnesota x Russet Burbank only for individual draws from the Bayesian hierarchical model, for the non-linear regression method, and for the approximation of the 90% credible region based on the posterior distribution of parameters *a* and *b*. For **(b)**, the solid red line represents individual draws (n=15) from the posterior distribution of the fitted Bayesian hierarchical model.

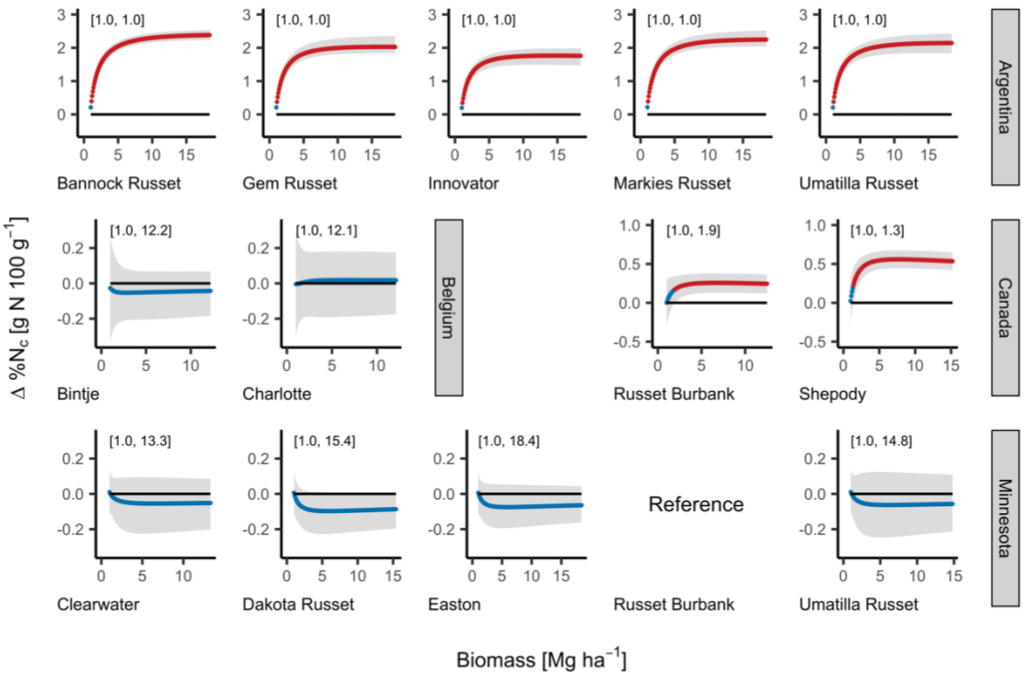


Figure 4-7. Comparison of the difference in critical N concentration values [$\Delta\%N_c$] between Russet Burbank x Minnesota and all other varieties within location for critical N concentration [$\%N_c$] determined by the hierarchical Bayesian method. The grey shaded region represents the 90% credible region (lower bound, 0.05 quantile; upper bound, 0.95 quantile) for $\Delta\%N_c$. The colored points represent the median value for $\Delta\%N_c$ at a given Biomass level where blue or red color respectively indicate that the credible region for $\Delta\%N_c$ does or does not contain zero. The solid black line at constant $\Delta\%N_c$ value of zero represents $\%N_c$ for the Russet Burbank x Minnesota reference curve. The range of biomass values for which $\Delta\%N_c$ is not significantly different (i.e., credible region contains zero) is given in brackets.

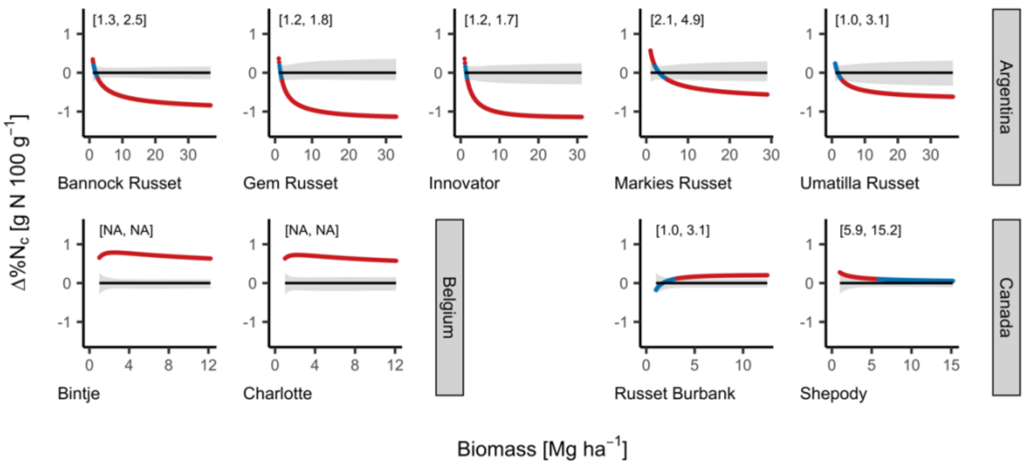


Figure 4-8. Comparison of the difference in critical N concentration values [$\Delta\%N_c$] between the conventional statistical methods used in previous studies (i.e., Argentina – Giletto and Echeverría (2015); Belgium – Ben Abdallah et al. (2016); Canada – Bélanger et al. (2001a)) and the hierarchical Bayesian method used in the present study for each variety within location. The grey shaded region represents the 90% credible region (lower bound, 0.05 quantile; upper bound, 0.95 quantile) for critical N concentration [$\%N_c$] from the hierarchical Bayesian method. The solid black line at a constant $\Delta\%N_c$ value of zero represents the median value for $\%N_c$ from the hierarchical Bayesian method. Red or blue points respectively indicate that $\Delta\%N_c$ falls outside of (i.e., is significant) or falls within (i.e., is not significant) the 90% credible region for $\%N_c$. The range of biomass values for which Δ%Nc in not significant is given in brackets.

4.8. TABLES

Table 4-1. Summary of experimental data used in this study.

Study	Location	Variety	Site-Years	Dates	Samples
Present Study	Minnesota	Clearwater	2	10	30
		Dakota Russet	2	14	70
		Easton	2	14	70
		Russet Burbank	9	52	328
		Umatilla Russet	2	10	30
Giletto et al. (2020)	Argentina	Bannock Russet	3	13	52
		Gem Russet	4	18	72
		Innovator	4	18	72
		Markies Russet	2	9	36
		Umatilla Russet	3	14	56
	Canada	Russet Burbank	4	30	104
		Shepody	4	30	105
Ben Abdallah et al. (2016)	Belgium	Bintje	17	49	238
		Charlotte	7	24	114

Table 4-2. Summary of newly reported experimental small-plot trials in Minnesota, USA.

Experiment	Year	Reference
MN-1	1991-1992	Errebhi et al. (1998a); Rosen et al. (1992); Rosen et al. (1993)
MN-2	2014-2015	Sun (2017); Sun et al. (2019)
MN-3	2016	Crants et al. (2017)
MN-4	2018-2019	Gupta and Rosen (2019); Gupta et al. (2020)
MN-5	2019	Bohman et al. (2020a)
MN-6	2020	Rosen et al. (2021)

Table 4-3. Summary of experimental treatments evaluated in small-plot trials in Minnesota, USA.

Experiment	N treatments†	N rates	Varieties
MN-1	10	0, 135, 180, 225, 270	Russet Burbank
MN-2	5	135, 200, 270, 335, 400	Russet Burbank, Dakota Russet, Easton
MN-3	4	45, 180, 245, 335	Russet Burbank
MN-4	3	135, 270, 400	Russet Burbank, Clearwater, Umatilla Russet
MN-5	8	45, 155, 245, 290, 335	Russet Burbank
MN-6	8	55, 155, 245, 270, 290, 335	Russet Burbank

† Including N source, timing, and placement combinations occurring at an equivalent N rate

Table 4-4. In-season and harvest sampling dates for the experimental small-plot trials in Minnesota, USA.

Experiment	Year	In-Season						Harvest
		1	2	3	4	5	6	
MN-1	1991	12 June	24 June	2 July	16 July	30 July	13 Aug	10 Sept.
MN-1	1992	10 June	25 June	17 July	5 Aug.	26 Aug.		15 Sept.
MN-2	2014	30 June	15 July	24 July	11 Aug.	26 Aug.	8 Sept.	15 Sept.
MN-2	2015	23 June	7 July	21 July	4 Aug.	17 Aug.	1 Sept.	16 Sept.
MN-3	2016	28 June	13 July	26 July	3 Aug.	10 Aug.		13 Sept.
MN-4	2018	26 June	10 July	18 July	1 Aug.			13 Sept.
MN-4	2019	26 June	11 July	24 July	7 Aug			16 Sept.
MN-5	2019	25 June	9 July	23 July	6 Aug	21 Aug		16 Sept.
MN-6	2020	24 June	7 July	22 July	4 Aug			16 Sept.

Table 4-5. Priors used in fitting the hierarchical Bayesian model with *brms*.

Parameter	Distribution	Bounds	
		Lower	Upper
a	Normal (5.3, 0.1)	0	∞
$\sigma(a_{location})$	Normal (0.10, 0.02)	–∞	∞
$\sigma(a_{location:variety})$	Normal (0.05, 0.01)	–∞	∞
b	Normal (0.40, 0.01)	0	1
$\sigma(b_{location})$	Normal (0.05, 0.02)	–∞	∞
$\sigma(b_{location:variety})$	Normal (0.02, 0.01)	–∞	∞
$Wmax$	Normal (8.0, 0.1)	1	∞
$\sigma(Wmax_{index})$	Normal (7.0, 1.0)	–∞	∞
S	Normal (6.0, 0.1)	0	∞
$\sigma(S_{index})$	Normal (1.0, 0.1)	–∞	∞
σ	Student's *t* (3, 1.0, 0.1)	–∞	∞

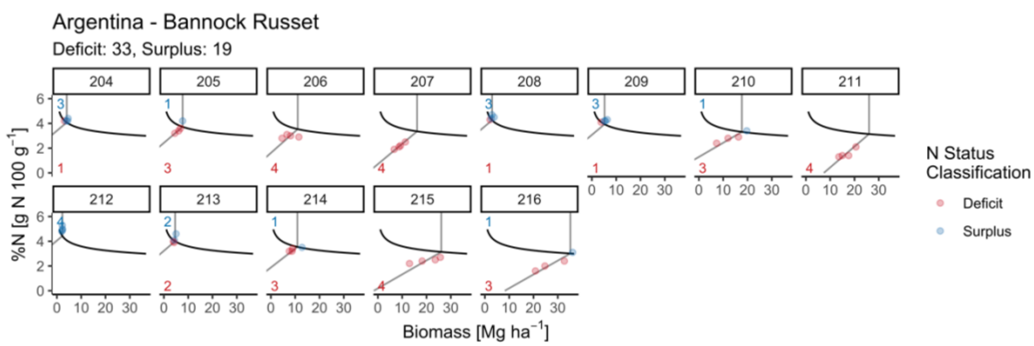
Table 4-6. Paired critical nitrogen dilution curve parameters for each variety within location for the median value (CNDC) from the posterior distribution of the fitted hierarchical Bayesian model and the estimates for the credible region lower ($CNDC_{lo}$) and upper ($CNDC_{up}$) boundaries using the non-linear regression method.

Location	Variety	$CNDC_{lo}$		CNDC		$CNDC_{up}$	
		a_{lo}	b_{lo}	a	b	a_{up}	b_{up}
Argentina	Bannock Russet	4.82	0.146	4.96	0.140	5.10	0.135
	Gem Russet	4.80	0.190	4.96	0.178	5.07	0.152
	Innovator	4.83	0.241	4.94	0.212	5.06	0.193
	Markies Russet	4.82	0.167	4.96	0.155	5.08	0.135
	Umatilla Russet	4.85	0.195	4.95	0.165	5.06	0.143
Belgium	Bintje	4.52	0.606	4.72	0.579	4.90	0.567
	Charlotte	4.56	0.607	4.74	0.559	4.89	0.531
Canada	Russet Burbank	4.53	0.498	4.74	0.489	4.93	0.480
	Shepody	4.55	0.416	4.77	0.412	4.95	0.406
Minnesota	Clearwater	4.56	0.622	4.75	0.585	4.93	0.558
	Dakota Russet	4.54	0.619	4.75	0.599	4.94	0.588
	Easton	4.54	0.608	4.75	0.592	4.91	0.567
	Russet Burbank	4.51	0.562	4.74	0.566	4.95	0.567
	Umatilla Russet	4.56	0.631	4.75	0.588	4.92	0.546

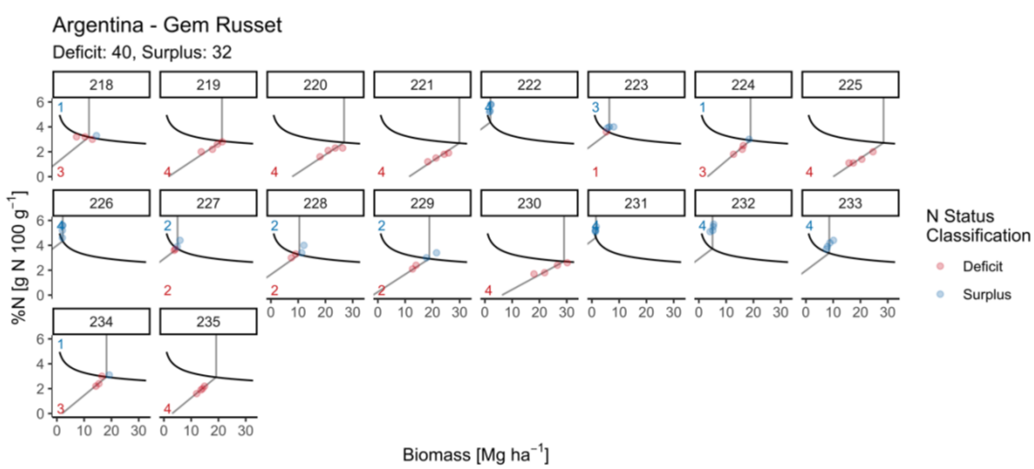
4.9. Supplemental Materials

Figure 4-S1. Fitted hierarchical Bayesian model shown for each level of variety within location: **(a)** Argentina x Bannock Russet, **(b)** Argentina x Gem Russet, **(c)** Argentina x Innovator, **(d)** Argentina x Markies Russet, **(e)** Argentina x Umatilla Russet, **(f)** Belgium x Bintje, **(g)** Belgium x Charlotte, **(h)** Canada x Russet Burbank, **(i)** Canada x Shepody, **(j)** Minnesota x Clearwater, **(k)** Minnesota x Dakota Russet, **(l)** Minnesota x Easton, **(m)** Minnesota x Russet Burbank, and **(n)** Minnesota x Russet Burbank. For each level of variety within location, the median fitted critical N concentration [$\%N_c$] is shown as the solid black line. Each level of index (i.e., experimental observation date, see Table 4-S1) nested within variety within location is shown as an individual panel, with the experimental data shown as either blue or red points and with the median fitted linear-plateau curve as a grey line. Experimental data were classified depending on whether the N concentration [%N] for that given level of biomass is less than the $\%N_c$ (i.e., Deficit) or is greater than $\%N_c$ (i.e., Surplus). The total number of experimental observations classified as Deficit (i.e., red points) or Surplus (i.e., blue points) is summarized for each level of index nested within variety within location and is also summarized for each level of variety within location.

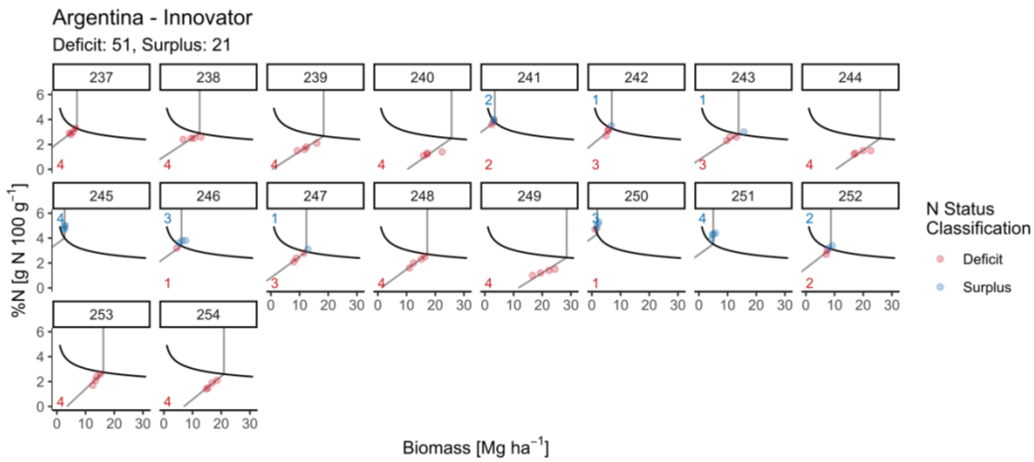
(a)



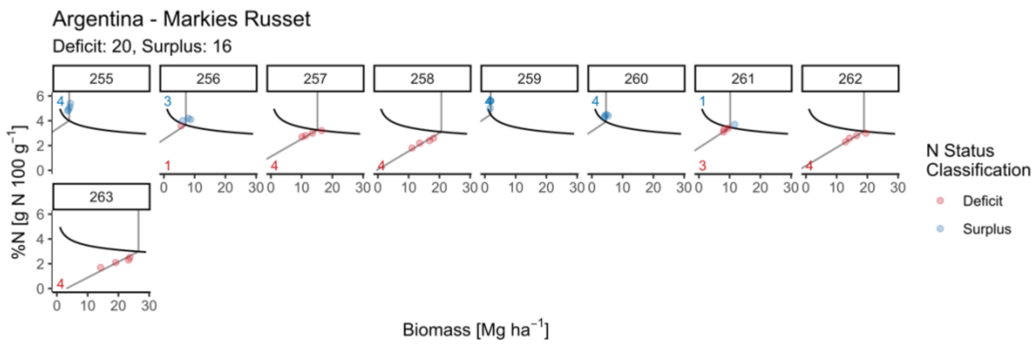
(b)



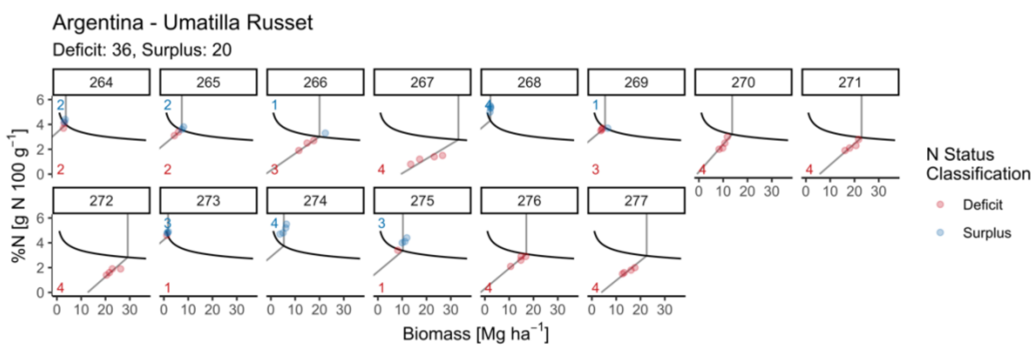
(c)


Argentina - Innovator
Deficit: 51, Surplus: 21
237
238
239
240
241
242
243
244
245
246
247
248
249
250
251
252
253
254
%N [g N 100 g^{-1}]
Biomass [Mg ha^{-1}]
N Status Classification
Deficit
Surplus

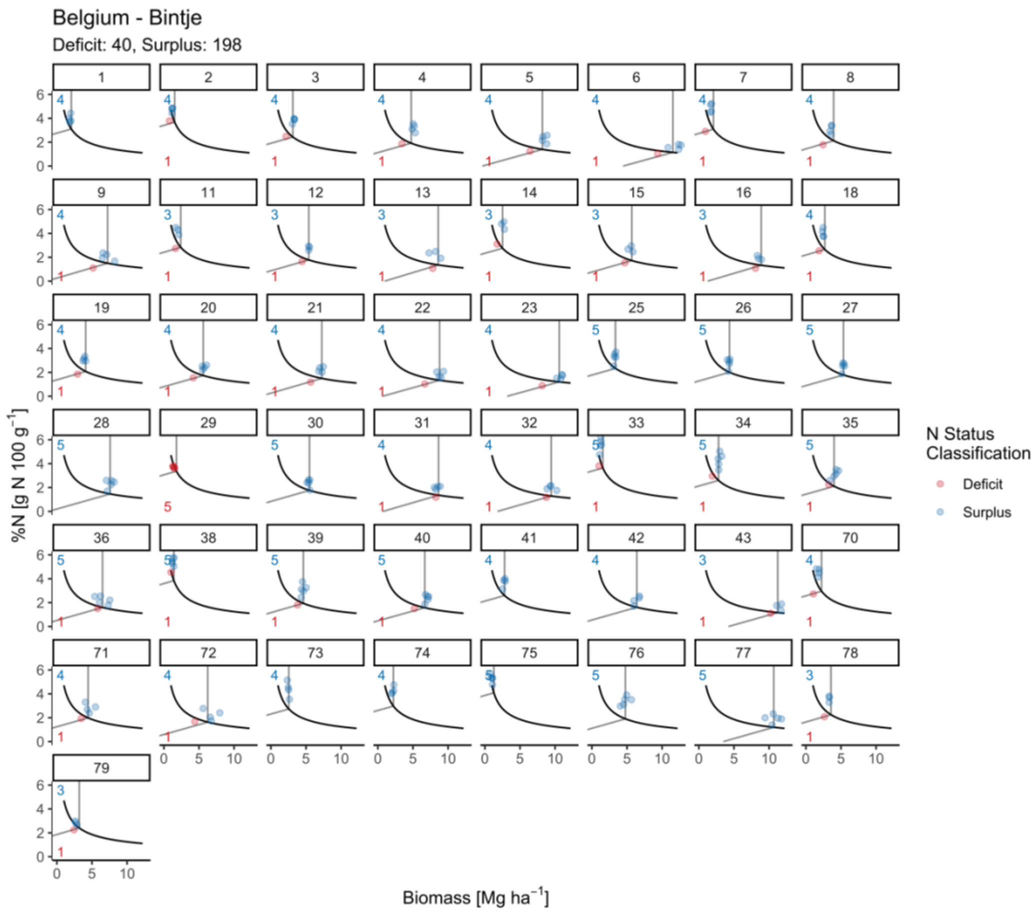
(d)


Argentina - Markies Russet
Deficit: 20, Surplus: 16
255
256
257
258
259
260
261
262
263
%N [g N 100 g^{-1}]
Biomass [Mg ha^{-1}]
N Status Classification
Deficit
Surplus

(e)

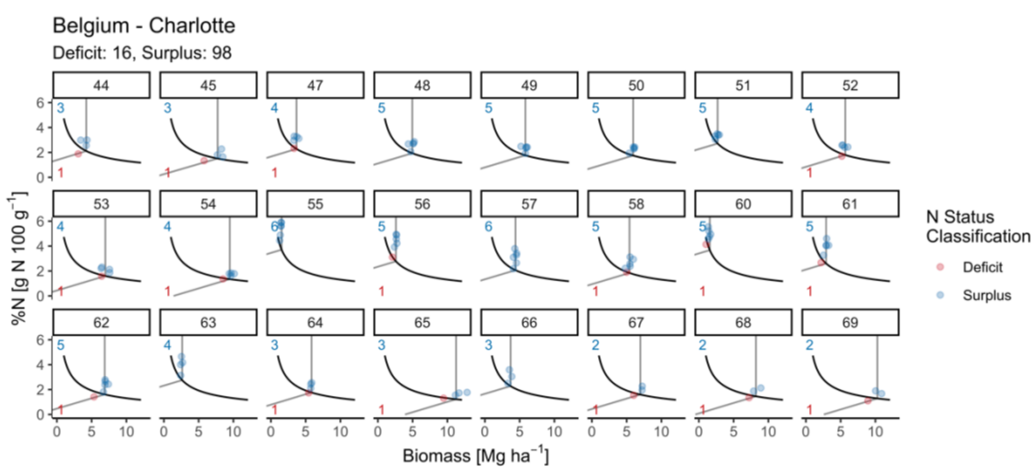

Argentina - Umatilla Russet
Deficit: 36, Surplus: 20
264
265
266
267
268
269
270
271
272
273
274
275
276
277
%N [g N 100 g^{-1}]
Biomass [Mg ha^{-1}]
N Status Classification
Deficit
Surplus

(f)



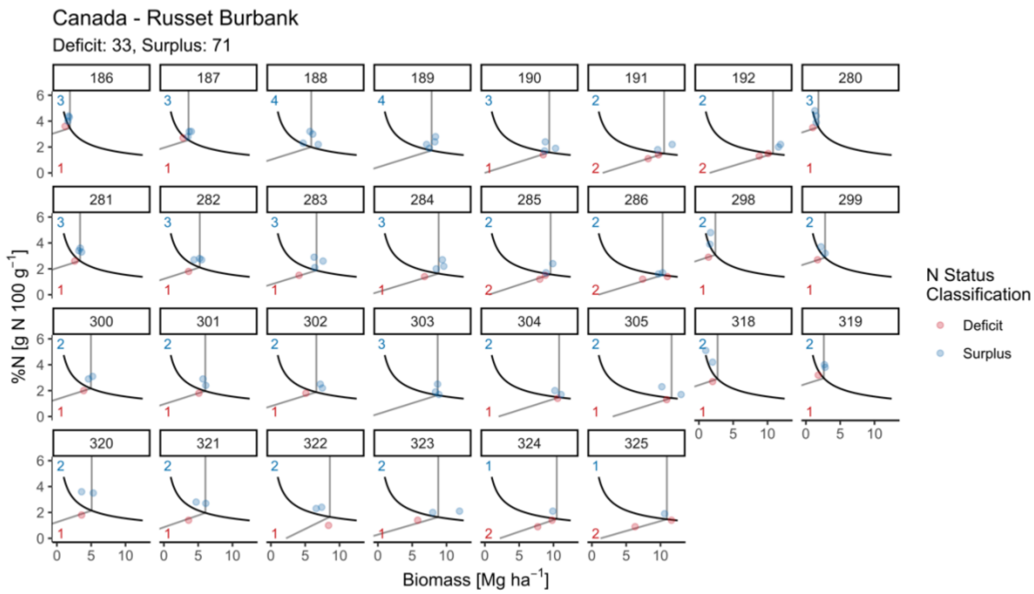
Belgium - Bintje
Deficit: 40, Surplus: 198
%N [g N 100 g^{-1}]
Biomass [Mg ha^{-1}]
N Status Classification
Deficit
Surplus

(g)

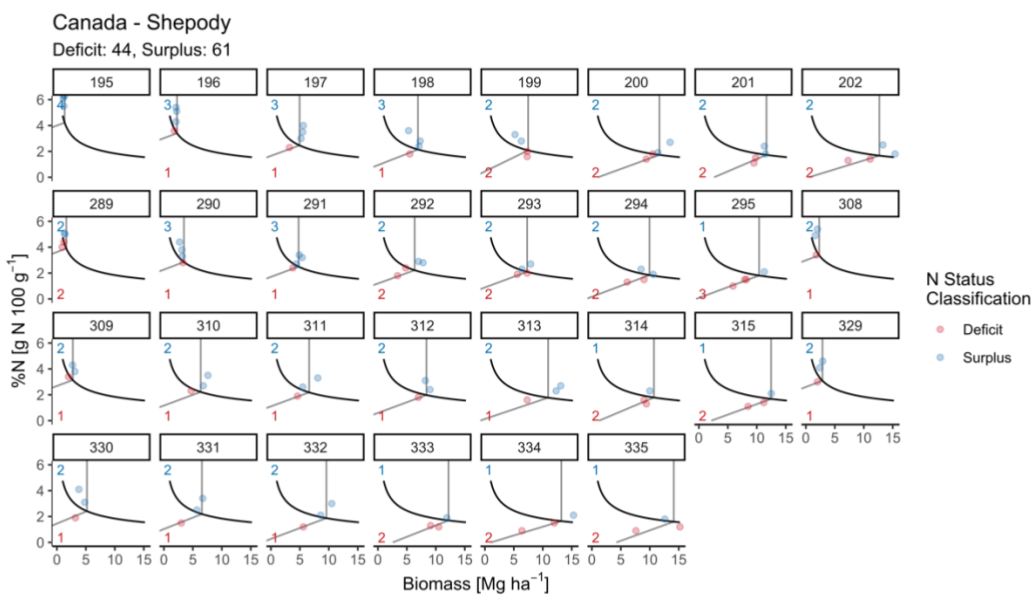


Belgium - Charlotte
Deficit: 16, Surplus: 98
%N [g N 100 g^{-1}]
Biomass [Mg ha^{-1}]
N Status Classification
Deficit
Surplus

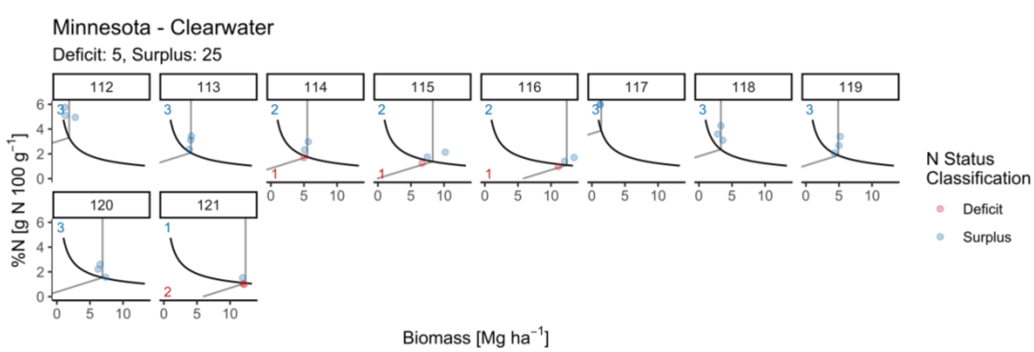
(h)


Canada - Russet Burbank
Deficit: 33, Surplus: 71
186 187 188 189 190 191 192 280
281 282 283 284 285 286 298 299
300 301 302 303 304 305 318 319
320 321 322 323 324 325
%N [g N 100 g^{-1}]
Biomass [Mg ha^{-1}]
N Status Classification
Deficit
Surplus

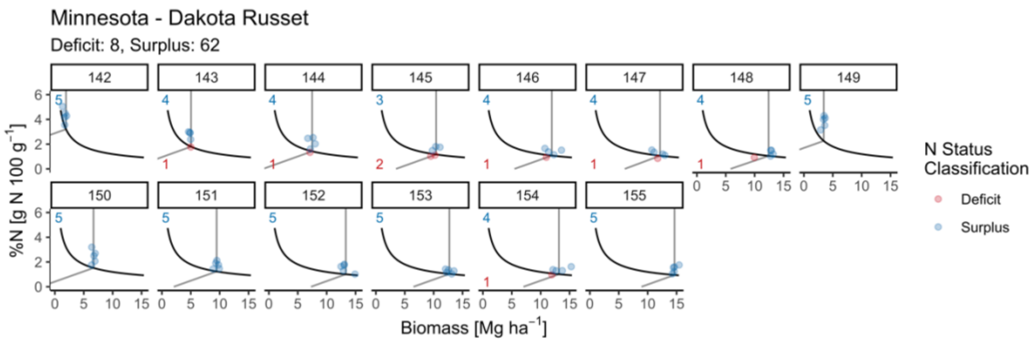
(i)


Canada - Shepody
Deficit: 44, Surplus: 61
195 196 197 198 199 200 201 202
289 290 291 292 293 294 295 308
309 310 311 312 313 314 315 329
330 331 332 333 334 335
%N [g N 100 g^{-1}]
Biomass [Mg ha^{-1}]
N Status Classification
Deficit
Surplus

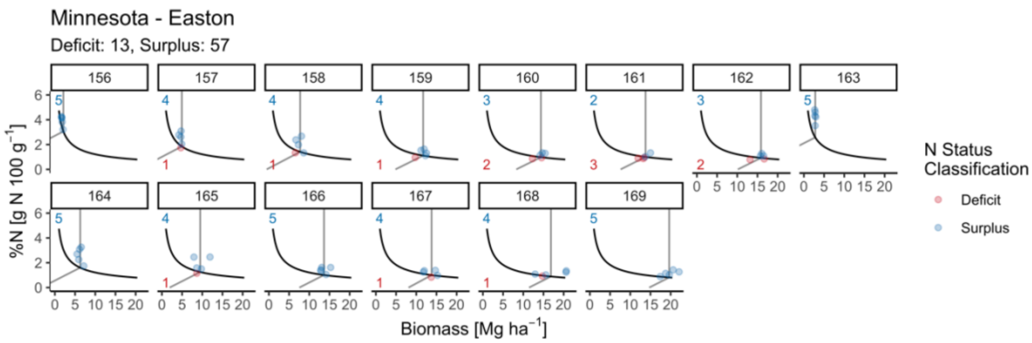
(j)


Minnesota - Clearwater
Deficit: 5, Surplus: 25
112 113 114 115 116 117 118 119
120 121
%N [g N 100 g^{-1}]
Biomass [Mg ha^{-1}]
N Status Classification
Deficit
Surplus

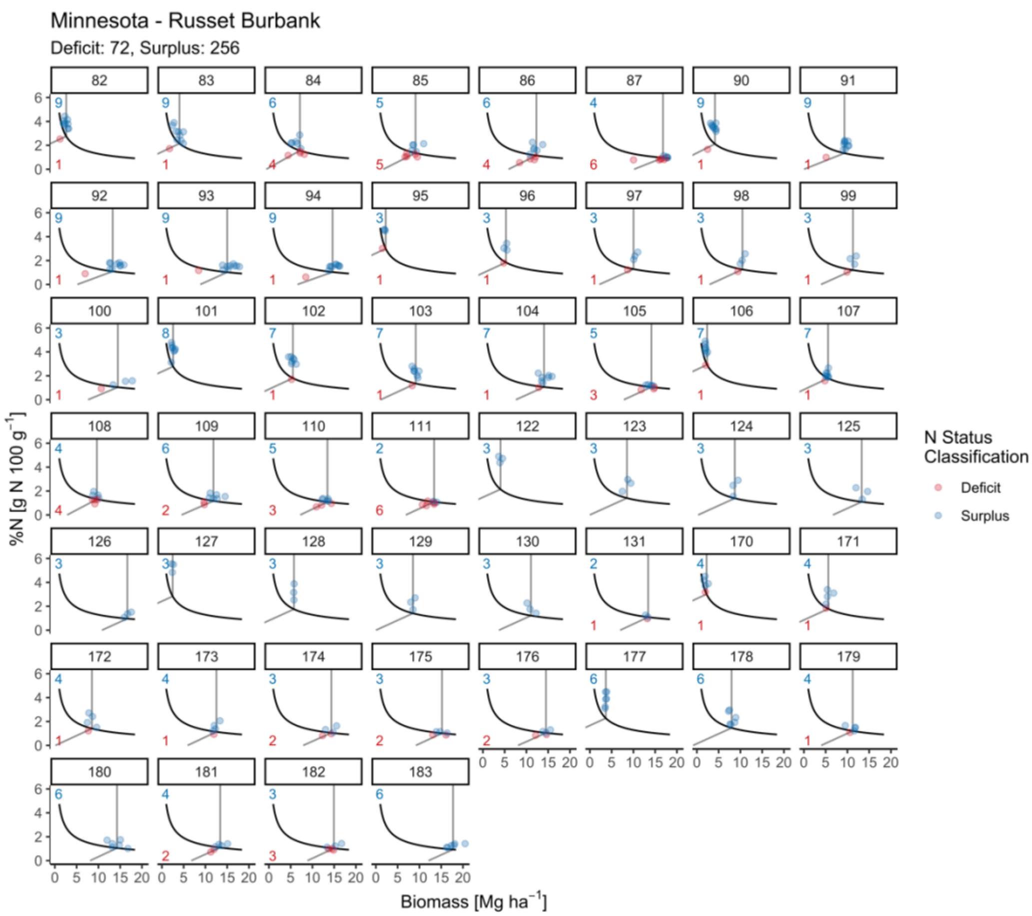
(k)


Minnesota - Dakota Russet
Deficit: 8, Surplus: 62
%N [g N 100 g^{-1}]
Biomass [Mg ha^{-1}]
N Status Classification
Deficit
Surplus

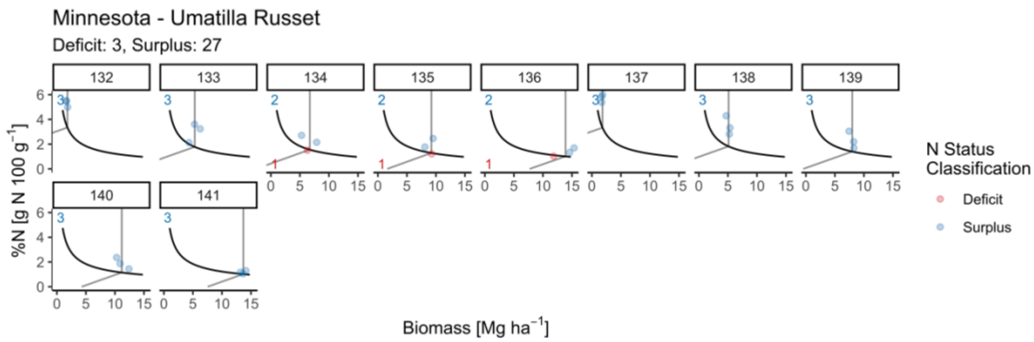
(l)


Minnesota - Easton
Deficit: 13, Surplus: 57
%N [g N 100 g^{-1}]
Biomass [Mg ha^{-1}]
N Status Classification
Deficit
Surplus

(m)


Minnesota - Russet Burbank
Deficit: 72, Surplus: 256
%N [g N 100 g^{-1}]
Biomass [Mg ha^{-1}]
N Status Classification
Deficit
Surplus

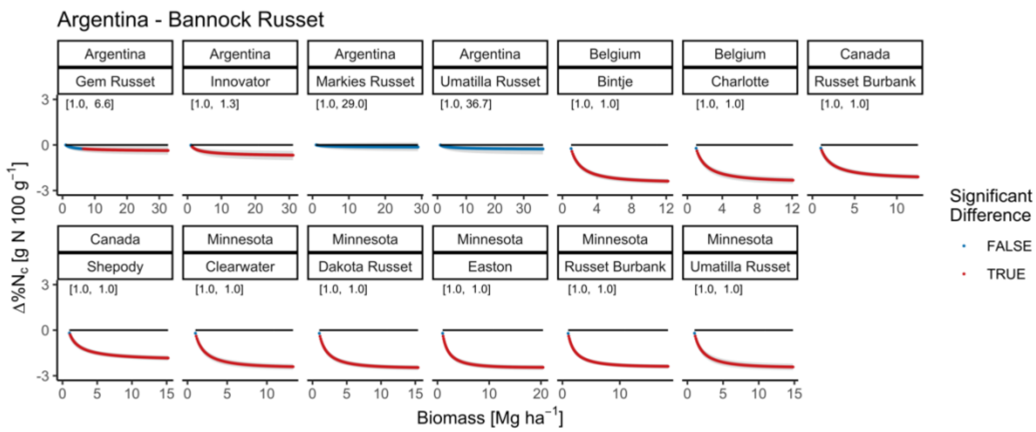
(n)



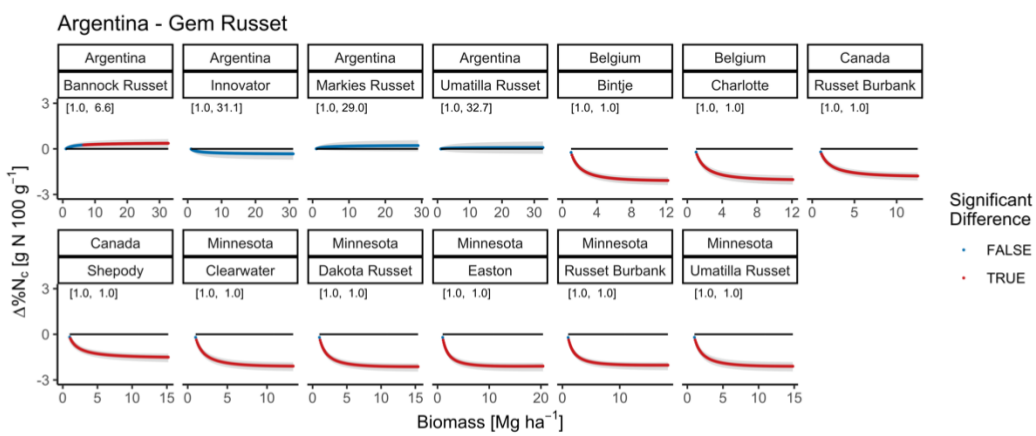
Minnesota - Umatilla Russet
Deficit: 3, Surplus: 27
132
133
134
135
136
137
138
139
140
141
%N [g N 100 g^{-1}]
Biomass [Mg ha^{-1}]
N Status Classification
Deficit
Surplus

Figure 4-S2. Pairwise comparison of the difference in critical N concentration values [$\Delta\%N_c$] between the critical N concentration [$\%N_c$] for a given reference curve and %Nc for all other levels of variety within location: **(a)** Argentina x Bannock Russet, **(b)** Argentina x Gem Russet, **(c)** Argentina x Innovator, **(d)** Argentina x Markies Russet, **(e)** Argentina x Umatilla Russet, **(f)** Belgium x Bintje, **(g)** Belgium x Charlotte, **(h)** Canada x Russet Burbank, **(i)** Canada x Shepody, **(j)** Minnesota x Clearwater, **(k)** Minnesota x Dakota Russet, **(l)** Minnesota x Easton, **(m)** Minnesota x Russet Burbank, and **(n)** Minnesota x Russet Burbank. The grey shaded region represents the 90% credible region (lower bound, 0.05 quantile; upper bound, 0.95 quantile) for $\Delta\%N_c$. The colored points represent the median value for $\Delta\%N_c$ at a given Biomass level where blue or red color respectively indicate that credible region for $\Delta\%N_c$ does or does not contain zero. The solid black line at constant value of zero represents $\%N_c$ for reference curve. The range of biomass values for which $\Delta\%N_c$ is not significantly different (i.e., credible region contains zero) is given in brackets.

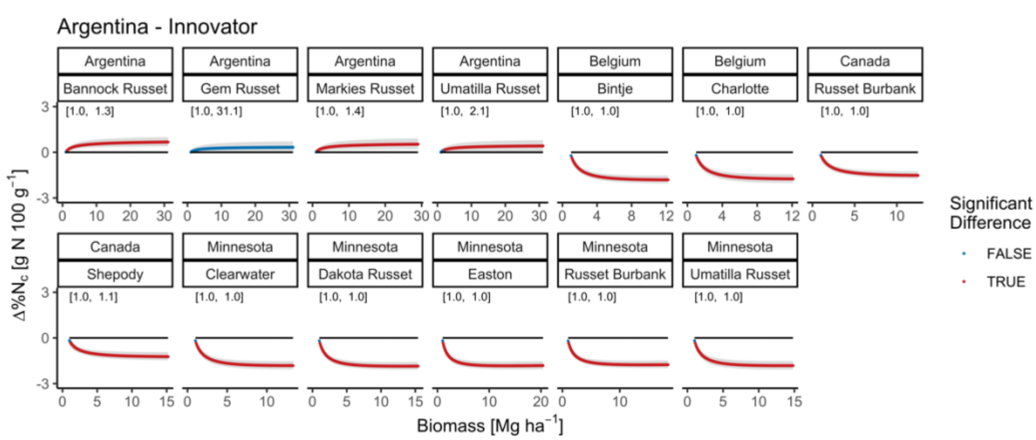
(a)



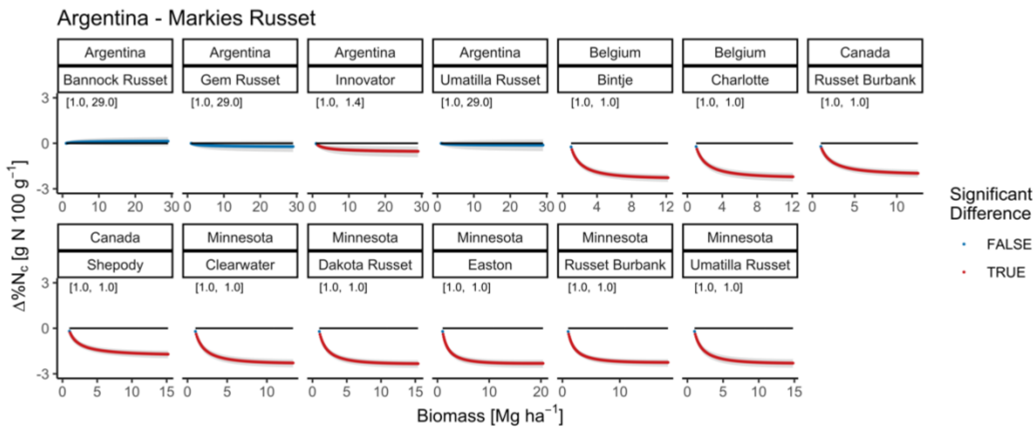
(b)



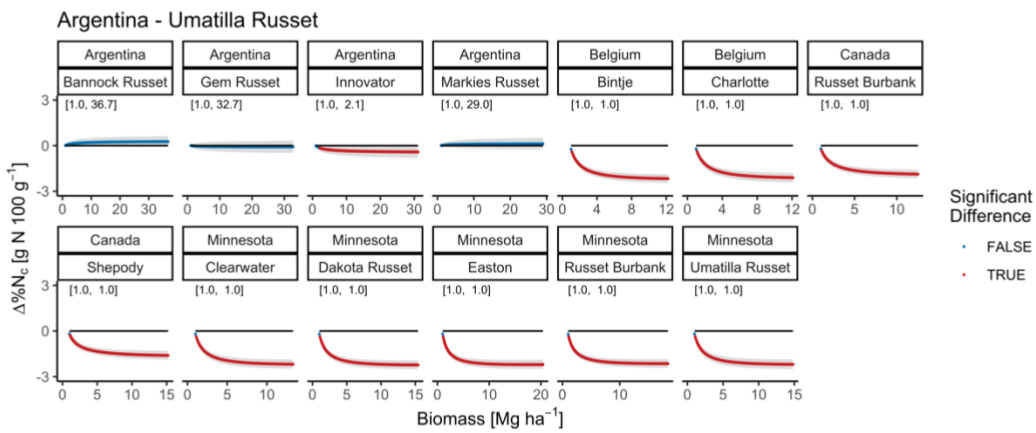
(c)



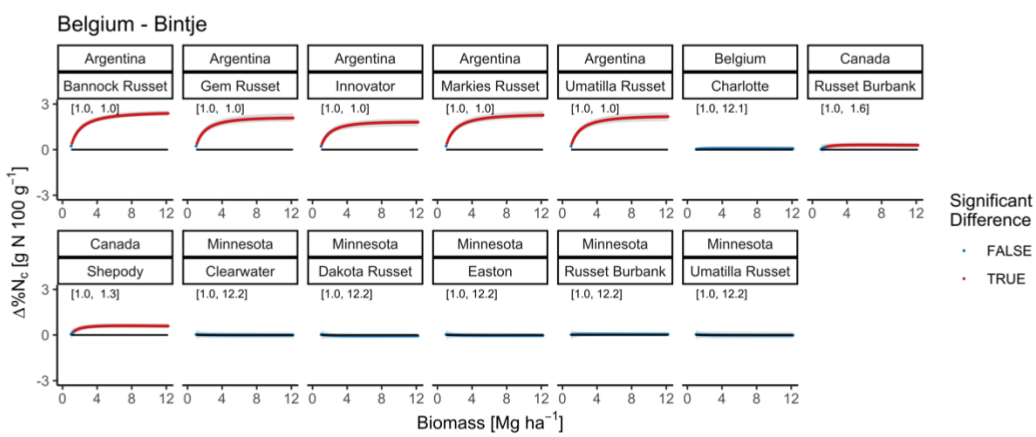
(d)


Argentina - Markies Russet
Argentina Bannock Russet [1.0, 29.0]
Argentina Gem Russet [1.0, 29.0]
Argentina Innovator [1.0, 1.4]
Argentina Umatilla Russet [1.0, 29.0]
Belgium Bintje [1.0, 1.0]
Belgium Charlotte [1.0, 1.0]
Canada Russet Burbank [1.0, 1.0]
Canada Shepody [1.0, 1.0]
Minnesota Clearwater [1.0, 1.0]
Minnesota Dakota Russet [1.0, 1.0]
Minnesota Easton [1.0, 1.0]
Minnesota Russet Burbank [1.0, 1.0]
Minnesota Umatilla Russet [1.0, 1.0]
Δ%Nc [g N 100 g⁻¹]
Biomass [Mg ha⁻¹]
Significant Difference
FALSE
TRUE

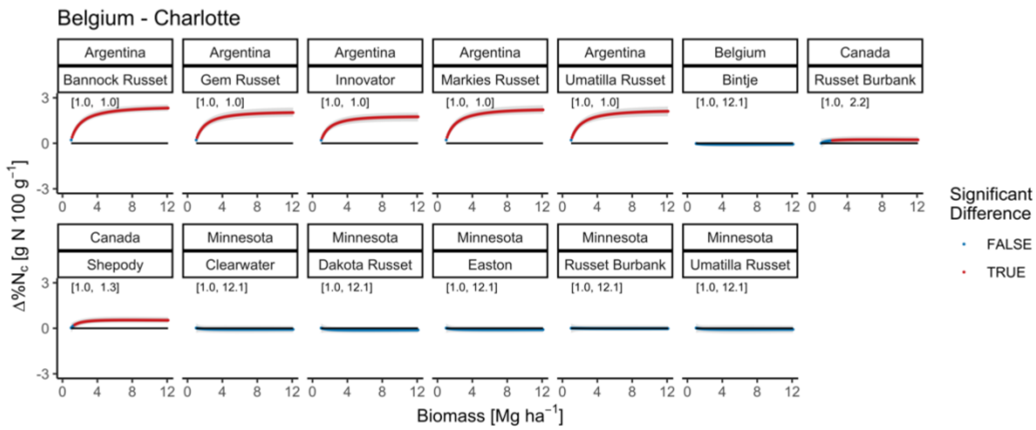
(e)


Argentina - Umatilla Russet
Argentina Bannock Russet [1.0, 36.7]
Argentina Gem Russet [1.0, 32.7]
Argentina Innovator [1.0, 2.1]
Argentina Markies Russet [1.0, 29.0]
Belgium Bintje [1.0, 1.0]
Belgium Charlotte [1.0, 1.0]
Canada Russet Burbank [1.0, 1.0]
Canada Shepody [1.0, 1.0]
Minnesota Clearwater [1.0, 1.0]
Minnesota Dakota Russet [1.0, 1.0]
Minnesota Easton [1.0, 1.0]
Minnesota Russet Burbank [1.0, 1.0]
Minnesota Umatilla Russet [1.0, 1.0]
Δ%Nc [g N 100 g⁻¹]
Biomass [Mg ha⁻¹]
Significant Difference
FALSE
TRUE

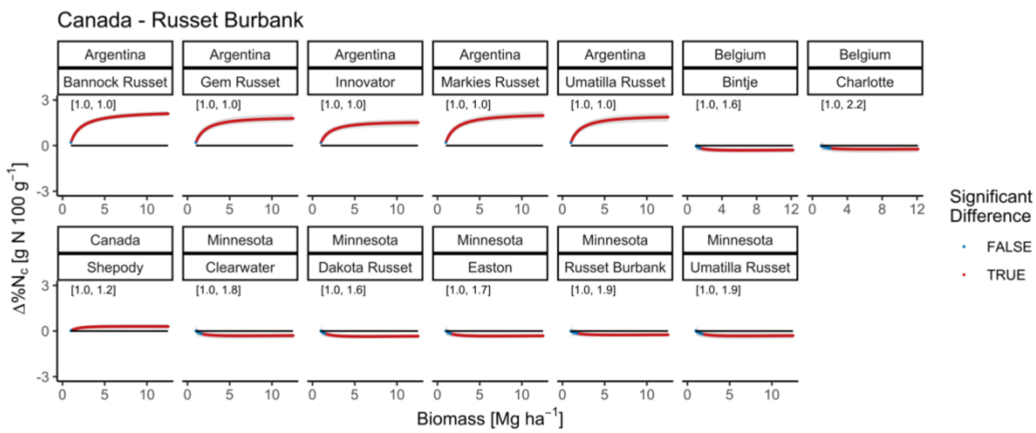
(f)


Belgium - Bintje
Argentina Bannock Russet [1.0, 1.0]
Argentina Gem Russet [1.0, 1.0]
Argentina Innovator [1.0, 1.0]
Argentina Markies Russet [1.0, 1.0]
Argentina Umatilla Russet [1.0, 1.0]
Belgium Charlotte [1.0, 12.1]
Canada Russet Burbank [1.0, 1.6]
Canada Shepody [1.0, 1.3]
Minnesota Clearwater [1.0, 12.2]
Minnesota Dakota Russet [1.0, 12.2]
Minnesota Easton [1.0, 12.2]
Minnesota Russet Burbank [1.0, 12.2]
Minnesota Umatilla Russet [1.0, 12.2]
Δ%Nc [g N 100 g⁻¹]
Biomass [Mg ha⁻¹]
Significant Difference
FALSE
TRUE

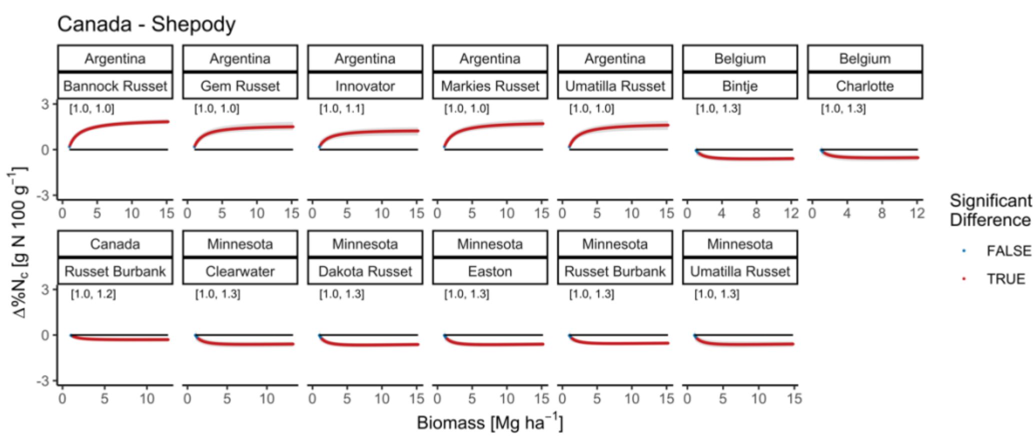
(g)


Belgium - Charlotte
Argentina Bannock Russet [1.0, 1.0]
Argentina Gem Russet [1.0, 1.0]
Argentina Innovator [1.0, 1.0]
Argentina Markies Russet [1.0, 1.0]
Argentina Umatilla Russet [1.0, 1.0]
Belgium Bintje [1.0, 12.1]
Canada Russet Burbank [1.0, 2.2]
Canada Shepody [1.0, 1.3]
Minnesota Clearwater [1.0, 12.1]
Minnesota Dakota Russet [1.0, 12.1]
Minnesota Easton [1.0, 12.1]
Minnesota Russet Burbank [1.0, 12.1]
Minnesota Umatilla Russet [1.0, 12.1]
Δ%Nc [g N 100 g⁻¹]
Biomass [Mg ha⁻¹]
Significant Difference
FALSE
TRUE

(h)


Canada - Russet Burbank
Argentina Bannock Russet [1.0, 1.0]
Argentina Gem Russet [1.0, 1.0]
Argentina Innovator [1.0, 1.0]
Argentina Markies Russet [1.0, 1.0]
Argentina Umatilla Russet [1.0, 1.0]
Belgium Bintje [1.0, 1.6]
Belgium Charlotte [1.0, 2.2]
Canada Shepody [1.0, 1.2]
Minnesota Clearwater [1.0, 1.8]
Minnesota Dakota Russet [1.0, 1.6]
Minnesota Easton [1.0, 1.7]
Minnesota Russet Burbank [1.0, 1.9]
Minnesota Umatilla Russet [1.0, 1.9]
Δ%Nc [g N 100 g⁻¹]
Biomass [Mg ha⁻¹]
Significant Difference
FALSE
TRUE

(i)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Argentina Gem Russet [1.0, 1.0]
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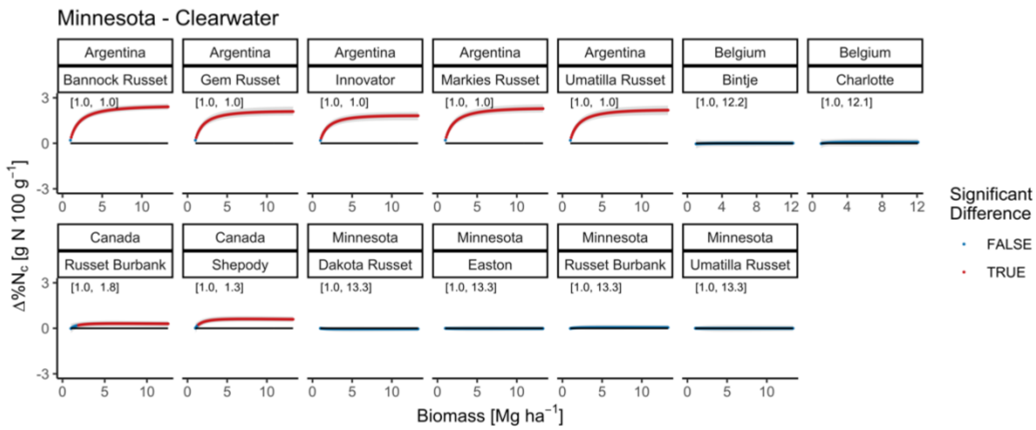
Argentina Markies Russet [1.0, 1.0]
Argentina Umatilla Russet [1.0, 1.0]
Belgium Bintje [1.0, 1.3]
Belgium Charlotte [1.0, 1.3]
Canada Russet Burbank [1.0, 1.2]
Minnesota Clearwater [1.0, 1.3]
Minnesota Dakota Russet [1.0, 1.3]
Minnesota Easton [1.0, 1.3]
Minnesota Russet Burbank [1.0, 1.3]
Minnesota Umatilla Russet [1.0, 1.3]
Δ%Nc [g N 100 g⁻¹]
Biomass [Mg ha⁻¹]
Significant Difference
FALSE
TRUE

(j)


Minnesota - Clearwater
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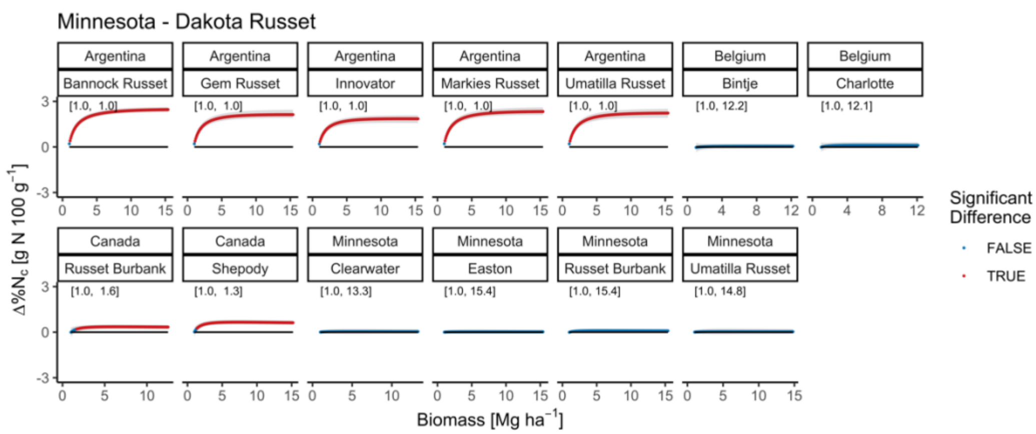
Argentina Innovator
Argentina Markies Russet
Argentina Umatilla Russet
Belgium Bintje
Belgium Charlotte
Canada Russet Burbank
Canada Shepody
Minnesota Dakota Russet
Minnesota Easton
Minnesota Russet Burbank
Minnesota Umatilla Russet
Δ%Nc [g N 100 g⁻¹]
Biomass [Mg ha⁻¹]
Significant Difference
FALSE
TRUE

(k)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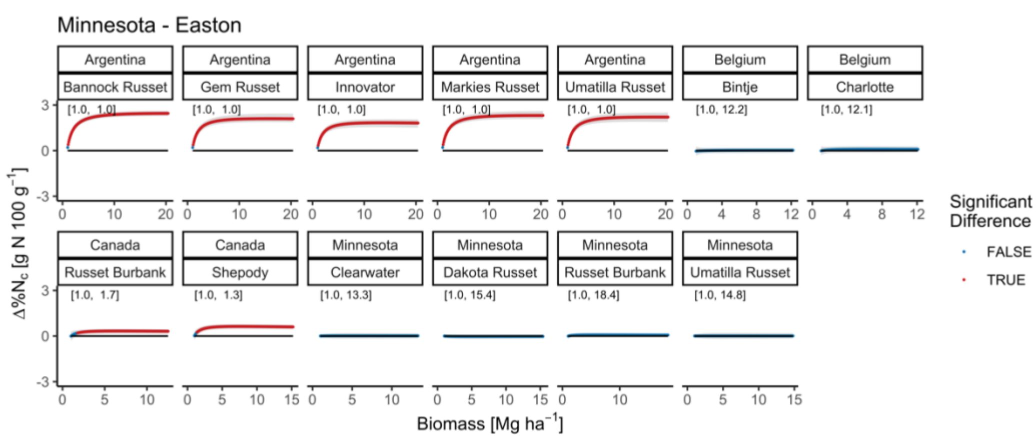
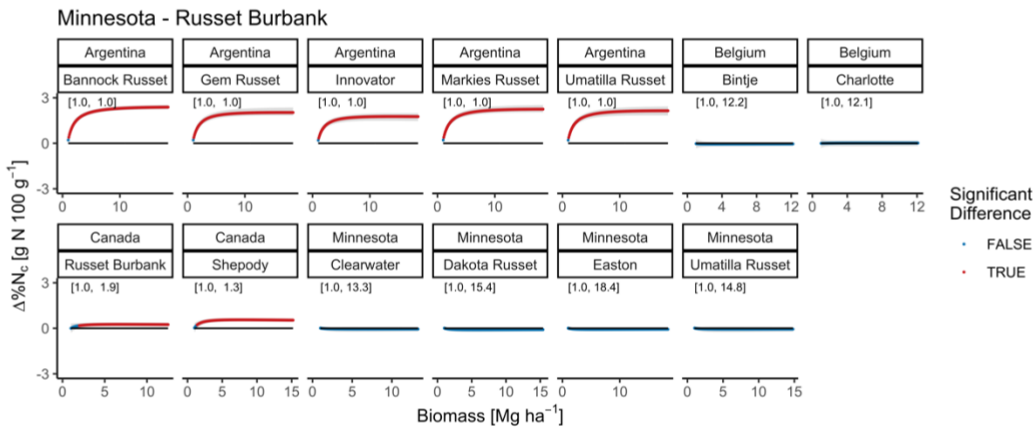
Argentina Bannock Russet
Argentina Gem Russet
Argentina Innovator
Argentina Markies Russet
Argentina Umatilla Russet
Belgium Bintje
Belgium Charlotte
Canada Russet Burbank
Canada Shepody
Minnesota Clearwater
Minnesota Easton
Minnesota Russet Burbank
Minnesota Umatilla Russet
Δ%Nc [g N 100 g⁻¹]
Biomass [Mg ha⁻¹]
Significant Difference
FALSE
TRUE

(l)


Minnesota - Easton
Argentina Bannock Russet
Argentina Gem Russet
Argentina Innovator
Argentina Markies Russet
Argentina Umatilla Russet
Belgium Bintje
Belgium Charlotte
Canada Russet Burbank
Canada Shepody
Minnesota Clearwater
Minnesota Dakota Russet
Minnesota Russet Burbank
Minnesota Umatilla Russet
Δ%Nc [g N 100 g⁻¹]
Biomass [Mg ha⁻¹]
Significant Difference
FALSE
TRUE

(m)


Minnesota - Russet Burbank
Argentina
Bannock Russet
Argentina
Gem Russet
Argentina
Innovator
Argentina
Markies Russet
Argentina
Umatilla Russet
Belgium
Bintje
Belgium
Charlotte
Canada
Russet Burbank
Canada
Shepody
Minnesota
Clearwater
Minnesota
Dakota Russet
Minnesota
Easton
Minnesota
Umatilla Russet
Δ%Nc [g N 100 g-1]
Biomass [Mg ha-1]
Significant Difference
FALSE
TRUE

(n)

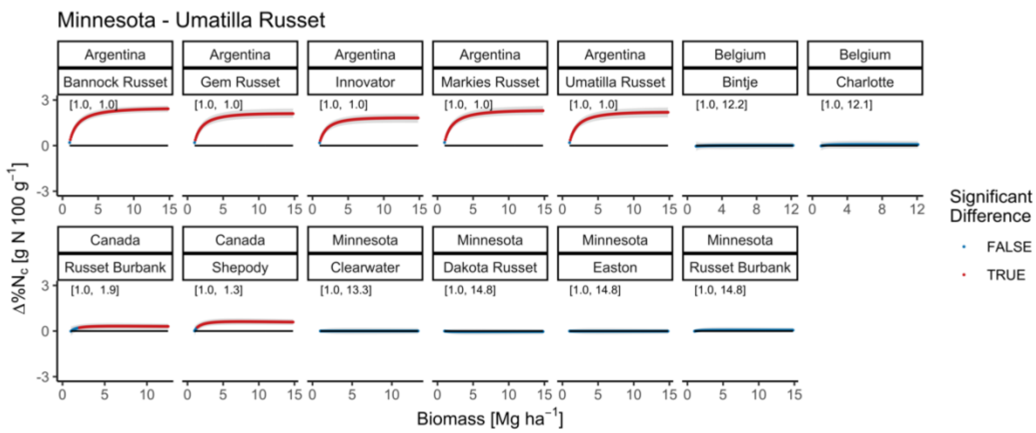

Minnesota - Umatilla Russet
Argentina
Bannock Russet
Argentina
Gem Russet
Argentina
Innovator
Argentina
Markies Russet
Argentina
Umatilla Russet
Belgium
Bintje
Belgium
Charlotte
Canada
Russet Burbank
Canada
Shepody
Minnesota
Clearwater
Minnesota
Dakota Russet
Minnesota
Easton
Minnesota
Russet Burbank
Δ%Nc [g N 100 g-1]
Biomass [Mg ha-1]
Significant Difference
FALSE
TRUE

Table 4-S1. Experimental data used to fit hierarchical Bayesian model.

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	%N_{Plant} g N 100 g^{-1}
1	Belgium	Bintje	1	1999-06-28	Franière	1999	0	1.87	3.68
2	Belgium	Bintje	1	1999-06-28	Franière	1999	119	2.00	3.81
3	Belgium	Bintje	1	1999-06-28	Franière	1999	170	1.75	3.97
4	Belgium	Bintje	1	1999-06-28	Franière	1999	221	1.97	4.43
5	Belgium	Bintje	2	1997-06-12	Gembloux	1997	0	0.79	3.78
6	Belgium	Bintje	2	1997-06-12	Gembloux	1997	75	1.15	4.45
7	Belgium	Bintje	2	1997-06-12	Gembloux	1997	113	1.14	4.80
8	Belgium	Bintje	2	1997-06-12	Gembloux	1997	150	1.20	4.85
9	Belgium	Bintje	2	1997-06-12	Gembloux	1997	188	1.25	4.84
10	Belgium	Bintje	3	1997-06-24	Gembloux	1997	0	2.17	2.49
11	Belgium	Bintje	3	1997-06-24	Gembloux	1997	75	3.08	3.53
12	Belgium	Bintje	3	1997-06-24	Gembloux	1997	113	3.38	3.89
13	Belgium	Bintje	3	1997-06-24	Gembloux	1997	150	3.33	3.92
14	Belgium	Bintje	3	1997-06-24	Gembloux	1997	188	3.31	3.99
15	Belgium	Bintje	4	1997-07-03	Gembloux	1997	0	3.42	1.88
16	Belgium	Bintje	4	1997-07-03	Gembloux	1997	75	5.32	2.79
17	Belgium	Bintje	4	1997-07-03	Gembloux	1997	113	4.87	3.10
18	Belgium	Bintje	4	1997-07-03	Gembloux	1997	150	5.19	3.35
19	Belgium	Bintje	4	1997-07-03	Gembloux	1997	188	5.03	3.53
20	Belgium	Bintje	5	1997-07-16	Gembloux	1997	0	6.44	1.25
21	Belgium	Bintje	5	1997-07-16	Gembloux	1997	75	8.82	1.86
22	Belgium	Bintje	5	1997-07-16	Gembloux	1997	113	8.17	2.15
23	Belgium	Bintje	5	1997-07-16	Gembloux	1997	150	8.25	2.46
24	Belgium	Bintje	5	1997-07-16	Gembloux	1997	188	8.84	2.57
25	Belgium	Bintje	6	1997-07-30	Gembloux	1997	0	9.37	1.04
26	Belgium	Bintje	6	1997-07-30	Gembloux	1997	75	12.36	1.39
27	Belgium	Bintje	6	1997-07-30	Gembloux	1997	113	10.85	1.55
28	Belgium	Bintje	6	1997-07-30	Gembloux	1997	150	12.34	1.81
29	Belgium	Bintje	6	1997-07-30	Gembloux	1997	188	12.71	1.76
30	Belgium	Bintje	7	1998-06-22	Gembloux	1998	0	0.93	2.90
31	Belgium	Bintje	7	1998-06-22	Gembloux	1998	88	1.78	4.58
32	Belgium	Bintje	7	1998-06-22	Gembloux	1998	132	1.66	4.50
33	Belgium	Bintje	7	1998-06-22	Gembloux	1998	176	1.82	5.23
34	Belgium	Bintje	7	1998-06-22	Gembloux	1998	220	1.66	5.14
35	Belgium	Bintje	8	1998-07-01	Gembloux	1998	0	2.44	1.78
36	Belgium	Bintje	8	1998-07-01	Gembloux	1998	88	3.59	2.67
37	Belgium	Bintje	8	1998-07-01	Gembloux	1998	132	3.41	2.91
38	Belgium	Bintje	8	1998-07-01	Gembloux	1998	176	3.66	3.41
39	Belgium	Bintje	8	1998-07-01	Gembloux	1998	220	3.66	3.36
40	Belgium	Bintje	9	1998-07-13	Gembloux	1998	0	5.16	1.10
41	Belgium	Bintje	9	1998-07-13	Gembloux	1998	88	8.23	1.67
42	Belgium	Bintje	9	1998-07-13	Gembloux	1998	132	6.48	1.92
43	Belgium	Bintje	9	1998-07-13	Gembloux	1998	176	6.58	2.36
44	Belgium	Bintje	9	1998-07-13	Gembloux	1998	220	7.08	2.23
45	Belgium	Bintje	11	1999-06-24	Gembloux	1999	0	1.66	2.73
46	Belgium	Bintje	11	1999-06-24	Gembloux	1999	119	2.12	3.89
47	Belgium	Bintje	11	1999-06-24	Gembloux	1999	170	1.72	4.49
48	Belgium	Bintje	11	1999-06-24	Gembloux	1999	221	2.00	4.30
49	Belgium	Bintje	12	1999-07-08	Gembloux	1999	0	4.44	1.64
50	Belgium	Bintje	12	1999-07-08	Gembloux	1999	119	5.39	2.59
51	Belgium	Bintje	12	1999-07-08	Gembloux	1999	170	5.50	2.84
52	Belgium	Bintje	12	1999-07-08	Gembloux	1999	221	5.38	2.94
53	Belgium	Bintje	13	1999-07-19	Gembloux	1999	0	7.82	1.07
54	Belgium	Bintje	13	1999-07-19	Gembloux	1999	119	8.96	1.92
55	Belgium	Bintje	13	1999-07-19	Gembloux	1999	170	7.29	2.36
56	Belgium	Bintje	13	1999-07-19	Gembloux	1999	221	8.24	2.49
57	Belgium	Bintje	14	2000-06-15	Gembloux	2000	0	1.75	3.11
58	Belgium	Bintje	14	2000-06-15	Gembloux	2000	102	2.78	4.34
59	Belgium	Bintje	14	2000-06-15	Gembloux	2000	145	2.38	4.79
60	Belgium	Bintje	14	2000-06-15	Gembloux	2000	189	2.71	4.97
61	Belgium	Bintje	15	2000-06-29	Gembloux	2000	0	4.69	1.53
62	Belgium	Bintje	15	2000-06-29	Gembloux	2000	102	5.83	2.46
63	Belgium	Bintje	15	2000-06-29	Gembloux	2000	145	5.15	2.68
64	Belgium	Bintje	15	2000-06-29	Gembloux	2000	189	5.62	2.95
65	Belgium	Bintje	16	2000-07-13	Gembloux	2000	0	8.06	1.08

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	%N_{Plant} g N 100 g^{-1}
66	Belgium	Bintje	16	2000-07-13	Gembloux	2000	102	8.92	1.81
67	Belgium	Bintje	16	2000-07-13	Gembloux	2000	145	8.32	2.14
68	Belgium	Bintje	16	2000-07-13	Gembloux	2000	189	8.49	1.89
69	Belgium	Bintje	18	2004-06-21	Gembloux	2004	0	1.88	2.54
70	Belgium	Bintje	18	2004-06-21	Gembloux	2004	100	2.49	3.77
71	Belgium	Bintje	18	2004-06-21	Gembloux	2004	140	2.52	3.75
72	Belgium	Bintje	18	2004-06-21	Gembloux	2004	180	2.45	4.48
73	Belgium	Bintje	18	2004-06-21	Gembloux	2004	240	2.37	4.16
74	Belgium	Bintje	19	2004-06-28	Gembloux	2004	0	2.94	1.85
75	Belgium	Bintje	19	2004-06-28	Gembloux	2004	100	4.10	2.96
76	Belgium	Bintje	19	2004-06-28	Gembloux	2004	140	3.73	2.97
77	Belgium	Bintje	19	2004-06-28	Gembloux	2004	180	3.85	3.15
78	Belgium	Bintje	19	2004-06-28	Gembloux	2004	240	3.99	3.34
79	Belgium	Bintje	20	2004-07-05	Gembloux	2004	0	4.19	1.54
80	Belgium	Bintje	20	2004-07-05	Gembloux	2004	100	5.53	2.22
81	Belgium	Bintje	20	2004-07-05	Gembloux	2004	140	5.78	2.39
82	Belgium	Bintje	20	2004-07-05	Gembloux	2004	180	5.46	2.52
83	Belgium	Bintje	20	2004-07-05	Gembloux	2004	240	6.08	2.60
84	Belgium	Bintje	21	2004-07-12	Gembloux	2004	0	5.67	1.18
85	Belgium	Bintje	21	2004-07-12	Gembloux	2004	100	7.29	2.00
86	Belgium	Bintje	21	2004-07-12	Gembloux	2004	140	6.82	2.11
87	Belgium	Bintje	21	2004-07-12	Gembloux	2004	180	6.98	2.39
88	Belgium	Bintje	21	2004-07-12	Gembloux	2004	240	7.47	2.48
89	Belgium	Bintje	22	2004-07-19	Gembloux	2004	0	6.70	1.03
90	Belgium	Bintje	22	2004-07-19	Gembloux	2004	100	9.01	1.57
91	Belgium	Bintje	22	2004-07-19	Gembloux	2004	140	8.73	1.65
92	Belgium	Bintje	22	2004-07-19	Gembloux	2004	180	8.39	2.03
93	Belgium	Bintje	22	2004-07-19	Gembloux	2004	240	9.35	2.08
94	Belgium	Bintje	23	2004-07-27	Gembloux	2004	0	8.16	0.88
95	Belgium	Bintje	23	2004-07-27	Gembloux	2004	100	10.81	1.47
96	Belgium	Bintje	23	2004-07-27	Gembloux	2004	140	10.24	1.52
97	Belgium	Bintje	23	2004-07-27	Gembloux	2004	180	11.06	1.73
98	Belgium	Bintje	23	2004-07-27	Gembloux	2004	240	10.98	1.82
99	Belgium	Bintje	25	2010-06-28	Gembloux	2010	0	3.10	2.53
100	Belgium	Bintje	25	2010-06-28	Gembloux	2010	115	3.19	3.29
101	Belgium	Bintje	25	2010-06-28	Gembloux	2010	165	3.42	3.28
102	Belgium	Bintje	25	2010-06-28	Gembloux	2010	215	3.22	3.50
103	Belgium	Bintje	25	2010-06-28	Gembloux	2010	248	3.42	3.72
104	Belgium	Bintje	26	2010-07-05	Gembloux	2010	0	4.20	2.10
105	Belgium	Bintje	26	2010-07-05	Gembloux	2010	115	4.33	2.71
106	Belgium	Bintje	26	2010-07-05	Gembloux	2010	165	4.34	2.92
107	Belgium	Bintje	26	2010-07-05	Gembloux	2010	215	4.06	3.05
108	Belgium	Bintje	26	2010-07-05	Gembloux	2010	248	4.41	3.11
109	Belgium	Bintje	27	2010-07-12	Gembloux	2010	0	5.12	1.87
110	Belgium	Bintje	27	2010-07-12	Gembloux	2010	115	5.50	2.53
111	Belgium	Bintje	27	2010-07-12	Gembloux	2010	165	5.24	2.55
112	Belgium	Bintje	27	2010-07-12	Gembloux	2010	215	5.43	2.74
113	Belgium	Bintje	27	2010-07-12	Gembloux	2010	248	5.27	2.78
114	Belgium	Bintje	28	2010-07-26	Gembloux	2010	0	7.19	1.70
115	Belgium	Bintje	28	2010-07-26	Gembloux	2010	115	7.72	2.25
116	Belgium	Bintje	28	2010-07-26	Gembloux	2010	165	8.15	2.46
117	Belgium	Bintje	28	2010-07-26	Gembloux	2010	215	7.07	2.59
118	Belgium	Bintje	28	2010-07-26	Gembloux	2010	248	7.80	2.58
119	Belgium	Bintje	29	2011-06-14	Gembloux	2011	0	1.44	3.76
120	Belgium	Bintje	29	2011-06-14	Gembloux	2011	98	1.46	3.62
121	Belgium	Bintje	29	2011-06-14	Gembloux	2011	140	1.27	3.75
122	Belgium	Bintje	29	2011-06-14	Gembloux	2011	182	1.55	3.60
123	Belgium	Bintje	29	2011-06-14	Gembloux	2011	210	1.36	3.77
124	Belgium	Bintje	30	2011-07-06	Gembloux	2011	0	5.55	1.79
125	Belgium	Bintje	30	2011-07-06	Gembloux	2011	98	5.15	2.42
126	Belgium	Bintje	30	2011-07-06	Gembloux	2011	140	5.41	2.39
127	Belgium	Bintje	30	2011-07-06	Gembloux	2011	182	5.37	2.62
128	Belgium	Bintje	30	2011-07-06	Gembloux	2011	210	5.53	2.64
129	Belgium	Bintje	31	2011-07-20	Gembloux	2011	0	8.26	1.19
130	Belgium	Bintje	31	2011-07-20	Gembloux	2011	98	8.25	1.84
131	Belgium	Bintje	31	2011-07-20	Gembloux	2011	140	8.04	2.01
132	Belgium	Bintje	31	2011-07-20	Gembloux	2011	182	8.88	2.10

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	$\%N_{Plant}$ g N 100 g^{-1}
133	Belgium	Bintje	31	2011-07-20	Gembloux	2011	210	8.53	2.07
134	Belgium	Bintje	32	2011-07-25	Gembloux	2011	0	8.77	1.17
135	Belgium	Bintje	32	2011-07-25	Gembloux	2011	98	10.22	1.76
136	Belgium	Bintje	32	2011-07-25	Gembloux	2011	140	8.86	1.89
137	Belgium	Bintje	32	2011-07-25	Gembloux	2011	182	9.42	2.15
138	Belgium	Bintje	32	2011-07-25	Gembloux	2011	210	9.30	2.11
139	Belgium	Bintje	33	2012-06-27	Gembloux	2012	0	1.02	3.81
140	Belgium	Bintje	33	2012-06-27	Gembloux	2012	50	1.10	4.74
141	Belgium	Bintje	33	2012-06-27	Gembloux	2012	100	1.21	5.50
142	Belgium	Bintje	33	2012-06-27	Gembloux	2012	150	1.37	5.57
143	Belgium	Bintje	33	2012-06-27	Gembloux	2012	200	1.28	6.20
144	Belgium	Bintje	33	2012-06-27	Gembloux	2012	250	1.32	5.87
145	Belgium	Bintje	34	2012-07-04	Gembloux	2012	0	1.91	2.96
146	Belgium	Bintje	34	2012-07-04	Gembloux	2012	50	2.83	3.47
147	Belgium	Bintje	34	2012-07-04	Gembloux	2012	100	2.83	3.96
148	Belgium	Bintje	34	2012-07-04	Gembloux	2012	150	2.75	4.41
149	Belgium	Bintje	34	2012-07-04	Gembloux	2012	200	3.25	4.61
150	Belgium	Bintje	34	2012-07-04	Gembloux	2012	250	2.97	5.04
151	Belgium	Bintje	35	2012-07-11	Gembloux	2012	0	3.25	2.25
152	Belgium	Bintje	35	2012-07-11	Gembloux	2012	50	3.41	2.59
153	Belgium	Bintje	35	2012-07-11	Gembloux	2012	100	4.00	2.95
154	Belgium	Bintje	35	2012-07-11	Gembloux	2012	150	4.28	3.13
155	Belgium	Bintje	35	2012-07-11	Gembloux	2012	200	4.29	3.50
156	Belgium	Bintje	35	2012-07-11	Gembloux	2012	250	4.66	3.40
157	Belgium	Bintje	36	2012-07-25	Gembloux	2012	0	5.82	1.50
158	Belgium	Bintje	36	2012-07-25	Gembloux	2012	50	7.31	1.78
159	Belgium	Bintje	36	2012-07-25	Gembloux	2012	100	6.06	2.02
160	Belgium	Bintje	36	2012-07-25	Gembloux	2012	150	7.54	2.21
161	Belgium	Bintje	36	2012-07-25	Gembloux	2012	200	5.40	2.51
162	Belgium	Bintje	36	2012-07-25	Gembloux	2012	250	6.21	2.54
163	Belgium	Bintje	38	2013-06-26	Gembloux	2013	0	1.00	4.54
164	Belgium	Bintje	38	2013-06-26	Gembloux	2013	50	1.41	5.04
165	Belgium	Bintje	38	2013-06-26	Gembloux	2013	100	1.16	5.46
166	Belgium	Bintje	38	2013-06-26	Gembloux	2013	150	1.45	5.77
167	Belgium	Bintje	38	2013-06-26	Gembloux	2013	200	1.23	5.28
168	Belgium	Bintje	38	2013-06-26	Gembloux	2013	250	1.29	5.72
169	Belgium	Bintje	39	2013-07-11	Gembloux	2013	0	3.79	1.80
170	Belgium	Bintje	39	2013-07-11	Gembloux	2013	50	4.33	2.45
171	Belgium	Bintje	39	2013-07-11	Gembloux	2013	100	4.35	3.12
172	Belgium	Bintje	39	2013-07-11	Gembloux	2013	150	4.64	2.97
173	Belgium	Bintje	39	2013-07-11	Gembloux	2013	200	5.04	3.25
174	Belgium	Bintje	39	2013-07-11	Gembloux	2013	250	4.50	3.75
175	Belgium	Bintje	40	2013-07-23	Gembloux	2013	0	5.19	1.50
176	Belgium	Bintje	40	2013-07-23	Gembloux	2013	50	6.67	1.86
177	Belgium	Bintje	40	2013-07-23	Gembloux	2013	100	7.14	2.27
178	Belgium	Bintje	40	2013-07-23	Gembloux	2013	150	7.21	2.49
179	Belgium	Bintje	40	2013-07-23	Gembloux	2013	200	7.13	2.52
180	Belgium	Bintje	40	2013-07-23	Gembloux	2013	250	6.76	2.67
181	Belgium	Bintje	41	2014-06-18	Gembloux	2014	0	2.51	3.14
182	Belgium	Bintje	41	2014-06-18	Gembloux	2014	100	2.91	3.80
183	Belgium	Bintje	41	2014-06-18	Gembloux	2014	200	2.85	4.01
184	Belgium	Bintje	41	2014-06-18	Gembloux	2014	250	2.67	3.86
185	Belgium	Bintje	42	2014-07-03	Gembloux	2014	0	5.99	1.71
186	Belgium	Bintje	42	2014-07-03	Gembloux	2014	100	5.99	2.17
187	Belgium	Bintje	42	2014-07-03	Gembloux	2014	200	6.75	2.40
188	Belgium	Bintje	42	2014-07-03	Gembloux	2014	250	6.76	2.55
189	Belgium	Bintje	43	2014-07-30	Gembloux	2014	0	10.23	1.11
190	Belgium	Bintje	43	2014-07-30	Gembloux	2014	100	11.70	1.33
191	Belgium	Bintje	43	2014-07-30	Gembloux	2014	200	11.10	1.75
192	Belgium	Bintje	43	2014-07-30	Gembloux	2014	250	11.77	1.88
193	Belgium	Charlotte	44	1999-07-06	Gembloux	1999	0	3.07	1.88
194	Belgium	Charlotte	44	1999-07-06	Gembloux	1999	84	3.43	2.99
195	Belgium	Charlotte	44	1999-07-06	Gembloux	1999	120	4.22	2.56
196	Belgium	Charlotte	44	1999-07-06	Gembloux	1999	156	4.32	2.99
197	Belgium	Charlotte	45	1999-07-22	Gembloux	1999	0	5.79	1.34
198	Belgium	Charlotte	45	1999-07-22	Gembloux	1999	84	8.47	1.64
199	Belgium	Charlotte	45	1999-07-22	Gembloux	1999	120	7.70	1.80

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	%N_{Plant} g N 100 g^{-1}
200	Belgium	Charlotte	45	1999-07-22	Gembloux	1999	156	8.29	2.27
201	Belgium	Charlotte	47	2010-07-01	Gembloux	2010	0	3.34	2.32
202	Belgium	Charlotte	47	2010-07-01	Gembloux	2010	100	4.01	3.13
203	Belgium	Charlotte	47	2010-07-01	Gembloux	2010	140	3.71	3.27
204	Belgium	Charlotte	47	2010-07-01	Gembloux	2010	180	3.30	2.96
205	Belgium	Charlotte	47	2010-07-01	Gembloux	2010	210	3.35	3.29
206	Belgium	Charlotte	48	2010-07-08	Gembloux	2010	0	4.72	2.06
207	Belgium	Charlotte	48	2010-07-08	Gembloux	2010	100	5.13	2.74
208	Belgium	Charlotte	48	2010-07-08	Gembloux	2010	140	4.38	2.68
209	Belgium	Charlotte	48	2010-07-08	Gembloux	2010	180	5.07	2.70
210	Belgium	Charlotte	48	2010-07-08	Gembloux	2010	210	5.22	2.87
211	Belgium	Charlotte	49	2010-07-15	Gembloux	2010	0	5.83	1.92
212	Belgium	Charlotte	49	2010-07-15	Gembloux	2010	100	5.91	2.35
213	Belgium	Charlotte	49	2010-07-15	Gembloux	2010	140	6.11	2.42
214	Belgium	Charlotte	49	2010-07-15	Gembloux	2010	180	5.19	2.48
215	Belgium	Charlotte	49	2010-07-15	Gembloux	2010	210	5.93	2.44
216	Belgium	Charlotte	50	2010-07-19	Gembloux	2010	0	5.36	1.94
217	Belgium	Charlotte	50	2010-07-19	Gembloux	2010	100	6.08	2.33
218	Belgium	Charlotte	50	2010-07-19	Gembloux	2010	140	6.05	2.29
219	Belgium	Charlotte	50	2010-07-19	Gembloux	2010	180	5.95	2.44
220	Belgium	Charlotte	50	2010-07-19	Gembloux	2010	210	6.16	2.44
221	Belgium	Charlotte	51	2011-06-20	Gembloux	2011	0	2.36	3.05
222	Belgium	Charlotte	51	2011-06-20	Gembloux	2011	84	2.64	3.50
223	Belgium	Charlotte	51	2011-06-20	Gembloux	2011	120	2.32	3.31
224	Belgium	Charlotte	51	2011-06-20	Gembloux	2011	156	2.77	3.39
225	Belgium	Charlotte	51	2011-06-20	Gembloux	2011	180	2.95	3.42
226	Belgium	Charlotte	52	2011-07-04	Gembloux	2011	0	5.17	1.70
227	Belgium	Charlotte	52	2011-07-04	Gembloux	2011	84	5.59	2.40
228	Belgium	Charlotte	52	2011-07-04	Gembloux	2011	120	5.32	2.59
229	Belgium	Charlotte	52	2011-07-04	Gembloux	2011	156	6.03	2.44
230	Belgium	Charlotte	52	2011-07-04	Gembloux	2011	180	5.19	2.57
231	Belgium	Charlotte	53	2011-07-11	Gembloux	2011	0	6.45	1.58
232	Belgium	Charlotte	53	2011-07-11	Gembloux	2011	84	7.60	1.87
233	Belgium	Charlotte	53	2011-07-11	Gembloux	2011	120	6.37	2.21
234	Belgium	Charlotte	53	2011-07-11	Gembloux	2011	156	7.57	2.13
235	Belgium	Charlotte	53	2011-07-11	Gembloux	2011	180	6.47	2.31
236	Belgium	Charlotte	54	2011-07-18	Gembloux	2011	0	8.51	1.36
237	Belgium	Charlotte	54	2011-07-18	Gembloux	2011	84	9.64	1.62
238	Belgium	Charlotte	54	2011-07-18	Gembloux	2011	120	9.40	1.79
239	Belgium	Charlotte	54	2011-07-18	Gembloux	2011	156	9.68	1.83
240	Belgium	Charlotte	54	2011-07-18	Gembloux	2011	180	10.13	1.78
241	Belgium	Charlotte	55	2012-06-27	Gembloux	2012	0	1.27	4.45
242	Belgium	Charlotte	55	2012-06-27	Gembloux	2012	50	1.35	4.88
243	Belgium	Charlotte	55	2012-06-27	Gembloux	2012	100	1.46	5.64
244	Belgium	Charlotte	55	2012-06-27	Gembloux	2012	150	1.49	5.90
245	Belgium	Charlotte	55	2012-06-27	Gembloux	2012	200	1.50	5.90
246	Belgium	Charlotte	55	2012-06-27	Gembloux	2012	250	1.46	5.59
247	Belgium	Charlotte	56	2012-07-02	Gembloux	2012	0	2.09	3.12
248	Belgium	Charlotte	56	2012-07-02	Gembloux	2012	50	2.38	3.93
249	Belgium	Charlotte	56	2012-07-02	Gembloux	2012	100	2.74	4.23
250	Belgium	Charlotte	56	2012-07-02	Gembloux	2012	150	2.64	4.57
251	Belgium	Charlotte	56	2012-07-02	Gembloux	2012	200	2.69	4.88
252	Belgium	Charlotte	56	2012-07-02	Gembloux	2012	250	2.63	4.95
253	Belgium	Charlotte	57	2012-07-09	Gembloux	2012	0	4.09	2.18
254	Belgium	Charlotte	57	2012-07-09	Gembloux	2012	50	4.54	2.65
255	Belgium	Charlotte	57	2012-07-09	Gembloux	2012	100	4.10	3.11
256	Belgium	Charlotte	57	2012-07-09	Gembloux	2012	150	4.54	3.28
257	Belgium	Charlotte	57	2012-07-09	Gembloux	2012	200	4.57	3.43
258	Belgium	Charlotte	57	2012-07-09	Gembloux	2012	250	4.30	3.79
259	Belgium	Charlotte	58	2012-07-16	Gembloux	2012	0	5.01	1.90
260	Belgium	Charlotte	58	2012-07-16	Gembloux	2012	50	4.80	2.22
261	Belgium	Charlotte	58	2012-07-16	Gembloux	2012	100	5.50	2.39
262	Belgium	Charlotte	58	2012-07-16	Gembloux	2012	150	5.47	2.58
263	Belgium	Charlotte	58	2012-07-16	Gembloux	2012	200	5.96	2.94
264	Belgium	Charlotte	58	2012-07-16	Gembloux	2012	250	5.49	3.12
265	Belgium	Charlotte	60	2013-06-24	Gembloux	2013	0	1.03	4.14
266	Belgium	Charlotte	60	2013-06-24	Gembloux	2013	50	1.37	4.57

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	%N_{Plant} g N 100 g^{-1}
267	Belgium	Charlotte	60	2013-06-24	Gembloux	2013	100	1.51	4.76
268	Belgium	Charlotte	60	2013-06-24	Gembloux	2013	150	1.43	5.22
269	Belgium	Charlotte	60	2013-06-24	Gembloux	2013	200	1.70	4.95
270	Belgium	Charlotte	60	2013-06-24	Gembloux	2013	250	1.36	5.55
271	Belgium	Charlotte	61	2013-07-01	Gembloux	2013	0	2.19	2.67
272	Belgium	Charlotte	61	2013-07-01	Gembloux	2013	50	2.53	3.27
273	Belgium	Charlotte	61	2013-07-01	Gembloux	2013	100	2.91	4.03
274	Belgium	Charlotte	61	2013-07-01	Gembloux	2013	150	2.94	4.08
275	Belgium	Charlotte	61	2013-07-01	Gembloux	2013	200	3.27	4.06
276	Belgium	Charlotte	61	2013-07-01	Gembloux	2013	250	2.98	4.60
277	Belgium	Charlotte	62	2013-07-15	Gembloux	2013	0	5.34	1.41
278	Belgium	Charlotte	62	2013-07-15	Gembloux	2013	50	6.70	1.81
279	Belgium	Charlotte	62	2013-07-15	Gembloux	2013	100	6.91	2.38
280	Belgium	Charlotte	62	2013-07-15	Gembloux	2013	150	7.41	2.43
281	Belgium	Charlotte	62	2013-07-15	Gembloux	2013	200	6.96	2.65
282	Belgium	Charlotte	62	2013-07-15	Gembloux	2013	250	6.94	2.79
283	Belgium	Charlotte	63	2014-06-16	Gembloux 1	2014	0	2.42	3.13
284	Belgium	Charlotte	63	2014-06-16	Gembloux 1	2014	100	2.41	4.00
285	Belgium	Charlotte	63	2014-06-16	Gembloux 1	2014	200	2.69	4.17
286	Belgium	Charlotte	63	2014-06-16	Gembloux 1	2014	250	2.53	4.65
287	Belgium	Charlotte	64	2014-06-30	Gembloux 1	2014	0	5.43	1.73
288	Belgium	Charlotte	64	2014-06-30	Gembloux 1	2014	100	5.73	2.10
289	Belgium	Charlotte	64	2014-06-30	Gembloux 1	2014	200	5.74	2.42
290	Belgium	Charlotte	64	2014-06-30	Gembloux 1	2014	250	5.87	2.55
291	Belgium	Charlotte	65	2014-07-28	Gembloux 1	2014	0	9.45	1.31
292	Belgium	Charlotte	65	2014-07-28	Gembloux 1	2014	100	11.16	1.55
293	Belgium	Charlotte	65	2014-07-28	Gembloux 1	2014	200	11.67	1.73
294	Belgium	Charlotte	65	2014-07-28	Gembloux 1	2014	250	12.83	1.77
295	Belgium	Charlotte	66	2014-06-24	Gembloux 2	2014	0	3.31	2.50
296	Belgium	Charlotte	66	2014-06-24	Gembloux 2	2014	100	3.87	3.05
297	Belgium	Charlotte	66	2014-06-24	Gembloux 2	2014	250	3.53	3.59
298	Belgium	Charlotte	67	2014-07-08	Gembloux 2	2014	0	6.02	1.53
299	Belgium	Charlotte	67	2014-07-08	Gembloux 2	2014	100	7.22	1.96
300	Belgium	Charlotte	67	2014-07-08	Gembloux 2	2014	250	7.24	2.27
301	Belgium	Charlotte	68	2014-07-15	Gembloux 2	2014	0	7.22	1.35
302	Belgium	Charlotte	68	2014-07-15	Gembloux 2	2014	100	7.88	1.88
303	Belgium	Charlotte	68	2014-07-15	Gembloux 2	2014	250	8.91	2.13
304	Belgium	Charlotte	69	2014-07-23	Gembloux 2	2014	0	8.92	1.10
305	Belgium	Charlotte	69	2014-07-23	Gembloux 2	2014	100	10.89	1.67
306	Belgium	Charlotte	69	2014-07-23	Gembloux 2	2014	250	10.03	1.89
307	Belgium	Bintje	70	1998-06-24	Gouy	1998	0	1.07	2.73
308	Belgium	Bintje	70	1998-06-24	Gouy	1998	88	1.73	4.13
309	Belgium	Bintje	70	1998-06-24	Gouy	1998	132	1.89	4.49
310	Belgium	Bintje	70	1998-06-24	Gouy	1998	176	1.90	4.77
311	Belgium	Bintje	70	1998-06-24	Gouy	1998	220	1.51	4.83
312	Belgium	Bintje	71	1998-07-07	Gouy	1998	0	3.47	1.94
313	Belgium	Bintje	71	1998-07-07	Gouy	1998	88	4.62	2.39
314	Belgium	Bintje	71	1998-07-07	Gouy	1998	132	4.33	2.69
315	Belgium	Bintje	71	1998-07-07	Gouy	1998	176	5.50	2.90
316	Belgium	Bintje	71	1998-07-07	Gouy	1998	220	4.06	3.31
317	Belgium	Bintje	72	1998-07-15	Gouy	1998	0	4.40	1.68
318	Belgium	Bintje	72	1998-07-15	Gouy	1998	88	6.75	1.74
319	Belgium	Bintje	72	1998-07-15	Gouy	1998	132	6.61	2.05
320	Belgium	Bintje	72	1998-07-15	Gouy	1998	176	7.97	2.41
321	Belgium	Bintje	72	1998-07-15	Gouy	1998	220	5.59	2.77
322	Belgium	Bintje	73	1999-06-28	incourt	1999	0	2.64	3.54
323	Belgium	Bintje	73	1999-06-28	incourt	1999	112	2.53	4.34
324	Belgium	Bintje	73	1999-06-28	incourt	1999	160	2.48	4.53
325	Belgium	Bintje	73	1999-06-28	incourt	1999	208	2.34	5.15
326	Belgium	Bintje	74	1999-07-01	Marcq	1999	0	1.96	4.04
327	Belgium	Bintje	74	1999-07-01	Marcq	1999	105	2.06	4.08
328	Belgium	Bintje	74	1999-07-01	Marcq	1999	150	2.24	4.26
329	Belgium	Bintje	74	1999-07-01	Marcq	1999	195	2.27	4.76
330	Belgium	Bintje	75	1997-06-10	Masnuy	1997	0	1.08	4.78
331	Belgium	Bintje	75	1997-06-10	Masnuy	1997	58	0.89	5.34
332	Belgium	Bintje	75	1997-06-10	Masnuy	1997	87	1.06	5.35
333	Belgium	Bintje	75	1997-06-10	Masnuy	1997	115	1.08	5.31

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	%N_{Plant} g N 100 g^{-1}
334	Belgium	Bintje	75	1997-06-10	Masnuy	1997	144	0.84	5.64
335	Belgium	Bintje	76	1997-07-01	Masnuy	1997	0	4.05	2.97
336	Belgium	Bintje	76	1997-07-01	Masnuy	1997	58	5.63	3.51
337	Belgium	Bintje	76	1997-07-01	Masnuy	1997	87	4.51	3.10
338	Belgium	Bintje	76	1997-07-01	Masnuy	1997	115	4.67	3.52
339	Belgium	Bintje	76	1997-07-01	Masnuy	1997	144	4.95	3.90
340	Belgium	Bintje	77	1997-07-24	Masnuy	1997	0	10.42	1.39
341	Belgium	Bintje	77	1997-07-24	Masnuy	1997	58	11.76	1.90
342	Belgium	Bintje	77	1997-07-24	Masnuy	1997	87	11.24	1.96
343	Belgium	Bintje	77	1997-07-24	Masnuy	1997	115	9.43	2.00
344	Belgium	Bintje	77	1997-07-24	Masnuy	1997	144	10.58	2.32
345	Belgium	Bintje	78	1999-06-28	Pontillas	1999	0	2.64	2.08
346	Belgium	Bintje	78	1999-06-28	Pontillas	1999	88	3.31	3.29
347	Belgium	Bintje	78	1999-06-28	Pontillas	1999	125	3.31	3.81
348	Belgium	Bintje	78	1999-06-28	Pontillas	1999	163	3.36	3.70
349	Belgium	Bintje	79	2000-07-19	Roisin	2000	0	2.43	2.25
350	Belgium	Bintje	79	2000-07-19	Roisin	2000	102	2.88	2.64
351	Belgium	Bintje	79	2000-07-19	Roisin	2000	145	2.68	2.83
352	Belgium	Bintje	79	2000-07-19	Roisin	2000	189	2.60	2.98
353	Minnesota	Russet Burbank	82	1991-06-24	MN-1	1991	0	1.17	2.53
354	Minnesota	Russet Burbank	82	1991-06-24	MN-1	1991	269	3.17	3.40
355	Minnesota	Russet Burbank	82	1991-06-24	MN-1	1991	269	2.28	4.44
356	Minnesota	Russet Burbank	82	1991-06-24	MN-1	1991	269	3.01	3.79
357	Minnesota	Russet Burbank	82	1991-06-24	MN-1	1991	269	2.94	3.39
358	Minnesota	Russet Burbank	82	1991-06-24	MN-1	1991	269	2.91	4.15
359	Minnesota	Russet Burbank	82	1991-06-24	MN-1	1991	179	2.35	3.85
360	Minnesota	Russet Burbank	82	1991-06-24	MN-1	1991	179	1.95	3.82
361	Minnesota	Russet Burbank	82	1991-06-24	MN-1	1991	135	2.26	3.71
362	Minnesota	Russet Burbank	82	1991-06-24	MN-1	1991	224	2.13	4.05
363	Minnesota	Russet Burbank	83	1991-07-02	MN-1	1991	0	1.76	1.72
364	Minnesota	Russet Burbank	83	1991-07-02	MN-1	1991	269	3.46	2.46
365	Minnesota	Russet Burbank	83	1991-07-02	MN-1	1991	269	2.78	3.90
366	Minnesota	Russet Burbank	83	1991-07-02	MN-1	1991	269	4.94	3.13
367	Minnesota	Russet Burbank	83	1991-07-02	MN-1	1991	269	3.79	3.14
368	Minnesota	Russet Burbank	83	1991-07-02	MN-1	1991	269	4.14	2.84
369	Minnesota	Russet Burbank	83	1991-07-02	MN-1	1991	179	2.47	3.67
370	Minnesota	Russet Burbank	83	1991-07-02	MN-1	1991	179	4.94	2.15
371	Minnesota	Russet Burbank	83	1991-07-02	MN-1	1991	135	4.42	2.40
372	Minnesota	Russet Burbank	83	1991-07-02	MN-1	1991	224	3.24	3.16
373	Minnesota	Russet Burbank	84	1991-07-16	MN-1	1991	0	4.42	1.16
374	Minnesota	Russet Burbank	84	1991-07-16	MN-1	1991	269	8.16	1.25
375	Minnesota	Russet Burbank	84	1991-07-16	MN-1	1991	269	7.08	2.87
376	Minnesota	Russet Burbank	84	1991-07-16	MN-1	1991	269	6.55	2.15
377	Minnesota	Russet Burbank	84	1991-07-16	MN-1	1991	269	5.11	2.19
378	Minnesota	Russet Burbank	84	1991-07-16	MN-1	1991	269	7.34	1.73
379	Minnesota	Russet Burbank	84	1991-07-16	MN-1	1991	179	6.20	2.30
380	Minnesota	Russet Burbank	84	1991-07-16	MN-1	1991	179	7.19	1.50
381	Minnesota	Russet Burbank	84	1991-07-16	MN-1	1991	135	7.19	1.36
382	Minnesota	Russet Burbank	84	1991-07-16	MN-1	1991	224	5.31	2.21
383	Minnesota	Russet Burbank	85	1991-07-30	MN-1	1991	0	6.71	1.03
384	Minnesota	Russet Burbank	85	1991-07-30	MN-1	1991	269	7.09	1.34
385	Minnesota	Russet Burbank	85	1991-07-30	MN-1	1991	269	8.47	2.04
386	Minnesota	Russet Burbank	85	1991-07-30	MN-1	1991	269	10.97	2.14
387	Minnesota	Russet Burbank	85	1991-07-30	MN-1	1991	269	8.22	1.56
388	Minnesota	Russet Burbank	85	1991-07-30	MN-1	1991	269	9.28	1.47
389	Minnesota	Russet Burbank	85	1991-07-30	MN-1	1991	179	7.13	1.08
390	Minnesota	Russet Burbank	85	1991-07-30	MN-1	1991	179	9.53	1.03
391	Minnesota	Russet Burbank	85	1991-07-30	MN-1	1991	135	9.07	1.26
392	Minnesota	Russet Burbank	85	1991-07-30	MN-1	1991	224	8.65	2.04
393	Minnesota	Russet Burbank	86	1991-08-13	MN-1	1991	0	8.44	0.55
394	Minnesota	Russet Burbank	86	1991-08-13	MN-1	1991	269	12.14	1.05
395	Minnesota	Russet Burbank	86	1991-08-13	MN-1	1991	269	11.39	2.26
396	Minnesota	Russet Burbank	86	1991-08-13	MN-1	1991	269	13.74	2.06
397	Minnesota	Russet Burbank	86	1991-08-13	MN-1	1991	269	11.75	1.75
398	Minnesota	Russet Burbank	86	1991-08-13	MN-1	1991	269	12.44	1.58
399	Minnesota	Russet Burbank	86	1991-08-13	MN-1	1991	179	11.70	1.66
400	Minnesota	Russet Burbank	86	1991-08-13	MN-1	1991	179	11.82	0.79

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	%N_{Plant} g N 100 g^{-1}
401	Minnesota	Russet Burbank	86	1991-08-13	MN-1	1991	135	10.88	0.86
402	Minnesota	Russet Burbank	86	1991-08-13	MN-1	1991	224	10.77	1.24
403	Minnesota	Russet Burbank	87	1991-09-05	MN-1	1991	0	10.02	0.78
404	Minnesota	Russet Burbank	87	1991-09-05	MN-1	1991	269	15.92	0.77
405	Minnesota	Russet Burbank	87	1991-09-05	MN-1	1991	269	17.62	1.05
406	Minnesota	Russet Burbank	87	1991-09-05	MN-1	1991	269	17.87	0.99
407	Minnesota	Russet Burbank	87	1991-09-05	MN-1	1991	269	17.40	0.93
408	Minnesota	Russet Burbank	87	1991-09-05	MN-1	1991	269	16.46	0.88
409	Minnesota	Russet Burbank	87	1991-09-05	MN-1	1991	179	17.86	0.96
410	Minnesota	Russet Burbank	87	1991-09-05	MN-1	1991	179	17.06	0.81
411	Minnesota	Russet Burbank	87	1991-09-05	MN-1	1991	135	16.25	0.85
412	Minnesota	Russet Burbank	87	1991-09-05	MN-1	1991	224	16.94	1.13
413	Minnesota	Russet Burbank	90	1992-06-25	MN-1	1992	0	2.46	1.66
414	Minnesota	Russet Burbank	90	1992-06-25	MN-1	1992	269	3.13	3.85
415	Minnesota	Russet Burbank	90	1992-06-25	MN-1	1992	269	3.72	3.49
416	Minnesota	Russet Burbank	90	1992-06-25	MN-1	1992	269	4.44	3.35
417	Minnesota	Russet Burbank	90	1992-06-25	MN-1	1992	269	3.60	3.64
418	Minnesota	Russet Burbank	90	1992-06-25	MN-1	1992	269	4.37	3.86
419	Minnesota	Russet Burbank	90	1992-06-25	MN-1	1992	179	3.38	3.70
420	Minnesota	Russet Burbank	90	1992-06-25	MN-1	1992	179	4.38	3.16
421	Minnesota	Russet Burbank	90	1992-06-25	MN-1	1992	135	3.85	3.56
422	Minnesota	Russet Burbank	90	1992-06-25	MN-1	1992	224	4.14	3.37
423	Minnesota	Russet Burbank	91	1992-07-17	MN-1	1992	0	5.12	1.00
424	Minnesota	Russet Burbank	91	1992-07-17	MN-1	1992	269	9.19	2.10
425	Minnesota	Russet Burbank	91	1992-07-17	MN-1	1992	269	9.38	2.40
426	Minnesota	Russet Burbank	91	1992-07-17	MN-1	1992	269	10.15	2.35
427	Minnesota	Russet Burbank	91	1992-07-17	MN-1	1992	269	9.32	2.33
428	Minnesota	Russet Burbank	91	1992-07-17	MN-1	1992	269	9.40	2.23
429	Minnesota	Russet Burbank	91	1992-07-17	MN-1	1992	179	10.30	1.97
430	Minnesota	Russet Burbank	91	1992-07-17	MN-1	1992	179	9.05	1.64
431	Minnesota	Russet Burbank	91	1992-07-17	MN-1	1992	135	9.57	1.69
432	Minnesota	Russet Burbank	91	1992-07-17	MN-1	1992	224	10.19	1.97
433	Minnesota	Russet Burbank	92	1992-08-05	MN-1	1992	0	6.96	0.90
434	Minnesota	Russet Burbank	92	1992-08-05	MN-1	1992	269	14.29	1.72
435	Minnesota	Russet Burbank	92	1992-08-05	MN-1	1992	269	14.82	1.82
436	Minnesota	Russet Burbank	92	1992-08-05	MN-1	1992	269	15.86	1.64
437	Minnesota	Russet Burbank	92	1992-08-05	MN-1	1992	269	12.59	1.81
438	Minnesota	Russet Burbank	92	1992-08-05	MN-1	1992	269	12.73	1.78
439	Minnesota	Russet Burbank	92	1992-08-05	MN-1	1992	179	15.00	1.55
440	Minnesota	Russet Burbank	92	1992-08-05	MN-1	1992	179	12.60	1.24
441	Minnesota	Russet Burbank	92	1992-08-05	MN-1	1992	135	13.20	1.28
442	Minnesota	Russet Burbank	92	1992-08-05	MN-1	1992	224	15.08	1.62
443	Minnesota	Russet Burbank	93	1992-08-26	MN-1	1992	0	8.44	1.17
444	Minnesota	Russet Burbank	93	1992-08-26	MN-1	1992	269	16.41	1.72
445	Minnesota	Russet Burbank	93	1992-08-26	MN-1	1992	269	13.94	1.62
446	Minnesota	Russet Burbank	93	1992-08-26	MN-1	1992	269	17.81	1.49
447	Minnesota	Russet Burbank	93	1992-08-26	MN-1	1992	269	14.99	1.51
448	Minnesota	Russet Burbank	93	1992-08-26	MN-1	1992	269	17.20	1.56
449	Minnesota	Russet Burbank	93	1992-08-26	MN-1	1992	179	16.68	1.54
450	Minnesota	Russet Burbank	93	1992-08-26	MN-1	1992	179	14.01	1.20
451	Minnesota	Russet Burbank	93	1992-08-26	MN-1	1992	135	15.22	1.26
452	Minnesota	Russet Burbank	93	1992-08-26	MN-1	1992	224	15.64	1.57
453	Minnesota	Russet Burbank	94	1992-09-08	MN-1	1992	0	8.47	0.62
454	Minnesota	Russet Burbank	94	1992-09-08	MN-1	1992	269	15.33	1.69
455	Minnesota	Russet Burbank	94	1992-09-08	MN-1	1992	269	16.29	1.53
456	Minnesota	Russet Burbank	94	1992-09-08	MN-1	1992	269	15.55	1.67
457	Minnesota	Russet Burbank	94	1992-09-08	MN-1	1992	269	16.00	1.54
458	Minnesota	Russet Burbank	94	1992-09-08	MN-1	1992	269	15.99	1.59
459	Minnesota	Russet Burbank	94	1992-09-08	MN-1	1992	179	14.22	1.52
460	Minnesota	Russet Burbank	94	1992-09-08	MN-1	1992	179	13.73	1.16
461	Minnesota	Russet Burbank	94	1992-09-08	MN-1	1992	135	13.98	1.49
462	Minnesota	Russet Burbank	94	1992-09-08	MN-1	1992	224	14.50	1.47
463	Minnesota	Russet Burbank	95	2016-06-27	MN-3	2016	45	1.50	3.02
464	Minnesota	Russet Burbank	95	2016-06-27	MN-3	2016	179	2.12	4.49
465	Minnesota	Russet Burbank	95	2016-06-27	MN-3	2016	336	1.98	4.60
466	Minnesota	Russet Burbank	95	2016-06-27	MN-3	2016	247	2.00	4.58
467	Minnesota	Russet Burbank	96	2016-07-12	MN-3	2016	45	4.80	1.80

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	%N_{Plant} g N 100 g^{-1}
468	Minnesota	Russet Burbank	96	2016-07-12	MN-3	2016	179	4.82	3.04
469	Minnesota	Russet Burbank	96	2016-07-12	MN-3	2016	336	5.46	3.44
470	Minnesota	Russet Burbank	96	2016-07-12	MN-3	2016	247	5.53	2.88
471	Minnesota	Russet Burbank	97	2016-07-25	MN-3	2016	45	8.67	1.22
472	Minnesota	Russet Burbank	97	2016-07-25	MN-3	2016	179	10.06	2.08
473	Minnesota	Russet Burbank	97	2016-07-25	MN-3	2016	336	11.01	2.70
474	Minnesota	Russet Burbank	97	2016-07-25	MN-3	2016	247	10.31	2.38
475	Minnesota	Russet Burbank	98	2016-08-02	MN-3	2016	45	9.41	1.08
476	Minnesota	Russet Burbank	98	2016-08-02	MN-3	2016	179	9.96	1.73
477	Minnesota	Russet Burbank	98	2016-08-02	MN-3	2016	336	11.08	2.57
478	Minnesota	Russet Burbank	98	2016-08-02	MN-3	2016	247	10.41	2.02
479	Minnesota	Russet Burbank	99	2016-08-09	MN-3	2016	45	9.91	1.03
480	Minnesota	Russet Burbank	99	2016-08-09	MN-3	2016	179	11.65	1.70
481	Minnesota	Russet Burbank	99	2016-08-09	MN-3	2016	336	12.03	2.38
482	Minnesota	Russet Burbank	99	2016-08-09	MN-3	2016	247	10.64	2.15
483	Minnesota	Russet Burbank	100	2016-09-13	MN-3	2016	45	10.66	0.92
484	Minnesota	Russet Burbank	100	2016-09-13	MN-3	2016	179	13.39	1.24
485	Minnesota	Russet Burbank	100	2016-09-13	MN-3	2016	336	16.22	1.54
486	Minnesota	Russet Burbank	100	2016-09-13	MN-3	2016	247	17.78	1.58
487	Minnesota	Russet Burbank	101	2020-06-24	MN-6	2020	56	2.16	3.12
488	Minnesota	Russet Burbank	101	2020-06-24	MN-6	2020	157	2.76	4.05
489	Minnesota	Russet Burbank	101	2020-06-24	MN-6	2020	336	2.26	4.57
490	Minnesota	Russet Burbank	101	2020-06-24	MN-6	2020	269	2.21	4.79
491	Minnesota	Russet Burbank	101	2020-06-24	MN-6	2020	291	3.05	4.25
492	Minnesota	Russet Burbank	101	2020-06-24	MN-6	2020	291	2.45	4.37
493	Minnesota	Russet Burbank	101	2020-06-24	MN-6	2020	291	2.97	4.13
494	Minnesota	Russet Burbank	101	2020-06-24	MN-6	2020	247	2.36	4.33
495	Minnesota	Russet Burbank	102	2020-07-07	MN-6	2020	56	5.21	1.70
496	Minnesota	Russet Burbank	102	2020-07-07	MN-6	2020	157	5.21	3.01
497	Minnesota	Russet Burbank	102	2020-07-07	MN-6	2020	336	5.11	3.60
498	Minnesota	Russet Burbank	102	2020-07-07	MN-6	2020	269	4.53	3.58
499	Minnesota	Russet Burbank	102	2020-07-07	MN-6	2020	291	6.28	2.97
500	Minnesota	Russet Burbank	102	2020-07-07	MN-6	2020	291	5.60	3.46
501	Minnesota	Russet Burbank	102	2020-07-07	MN-6	2020	291	5.81	3.34
502	Minnesota	Russet Burbank	102	2020-07-07	MN-6	2020	247	5.27	3.18
503	Minnesota	Russet Burbank	103	2020-07-22	MN-6	2020	56	8.35	1.18
504	Minnesota	Russet Burbank	103	2020-07-22	MN-6	2020	157	9.65	1.83
505	Minnesota	Russet Burbank	103	2020-07-22	MN-6	2020	336	8.32	2.79
506	Minnesota	Russet Burbank	103	2020-07-22	MN-6	2020	269	8.71	2.41
507	Minnesota	Russet Burbank	103	2020-07-22	MN-6	2020	291	9.89	2.39
508	Minnesota	Russet Burbank	103	2020-07-22	MN-6	2020	291	8.87	2.37
509	Minnesota	Russet Burbank	103	2020-07-22	MN-6	2020	291	8.82	2.58
510	Minnesota	Russet Burbank	103	2020-07-22	MN-6	2020	247	9.47	2.03
511	Minnesota	Russet Burbank	104	2020-08-04	MN-6	2020	56	12.84	1.02
512	Minnesota	Russet Burbank	104	2020-08-04	MN-6	2020	157	13.80	1.42
513	Minnesota	Russet Burbank	104	2020-08-04	MN-6	2020	336	12.72	2.22
514	Minnesota	Russet Burbank	104	2020-08-04	MN-6	2020	269	13.62	1.85
515	Minnesota	Russet Burbank	104	2020-08-04	MN-6	2020	291	15.03	1.86
516	Minnesota	Russet Burbank	104	2020-08-04	MN-6	2020	291	15.89	1.95
517	Minnesota	Russet Burbank	104	2020-08-04	MN-6	2020	291	15.11	2.02
518	Minnesota	Russet Burbank	104	2020-08-04	MN-6	2020	247	13.47	1.56
519	Minnesota	Russet Burbank	105	2020-09-15	MN-6	2020	56	11.77	0.83
520	Minnesota	Russet Burbank	105	2020-09-15	MN-6	2020	157	14.68	0.91
521	Minnesota	Russet Burbank	105	2020-09-15	MN-6	2020	336	13.41	1.26
522	Minnesota	Russet Burbank	105	2020-09-15	MN-6	2020	269	14.03	1.18
523	Minnesota	Russet Burbank	105	2020-09-15	MN-6	2020	291	14.58	1.17
524	Minnesota	Russet Burbank	105	2020-09-15	MN-6	2020	291	14.27	1.15
525	Minnesota	Russet Burbank	105	2020-09-15	MN-6	2020	291	12.87	1.22
526	Minnesota	Russet Burbank	105	2020-09-15	MN-6	2020	247	14.87	1.03
527	Minnesota	Russet Burbank	106	2019-06-25	MN-5	2019	45	2.03	2.88
528	Minnesota	Russet Burbank	106	2019-06-25	MN-5	2019	157	2.43	3.99
529	Minnesota	Russet Burbank	106	2019-06-25	MN-5	2019	247	1.98	4.29
530	Minnesota	Russet Burbank	106	2019-06-25	MN-5	2019	336	1.91	4.89
531	Minnesota	Russet Burbank	106	2019-06-25	MN-5	2019	157	2.05	4.36
532	Minnesota	Russet Burbank	106	2019-06-25	MN-5	2019	247	2.11	3.85
533	Minnesota	Russet Burbank	106	2019-06-25	MN-5	2019	336	1.99	4.67
534	Minnesota	Russet Burbank	106	2019-06-25	MN-5	2019	291	1.98	4.13

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	%N$_{Plant}$ g N 100 g^{-1}
535	Minnesota	Russet Burbank	107	2019-07-09	MN-5	2019	45	4.82	1.58
536	Minnesota	Russet Burbank	107	2019-07-09	MN-5	2019	157	5.65	1.92
537	Minnesota	Russet Burbank	107	2019-07-09	MN-5	2019	247	5.39	2.21
538	Minnesota	Russet Burbank	107	2019-07-09	MN-5	2019	336	5.65	2.66
539	Minnesota	Russet Burbank	107	2019-07-09	MN-5	2019	157	5.32	1.97
540	Minnesota	Russet Burbank	107	2019-07-09	MN-5	2019	247	5.57	1.88
541	Minnesota	Russet Burbank	107	2019-07-09	MN-5	2019	336	4.96	2.00
542	Minnesota	Russet Burbank	107	2019-07-09	MN-5	2019	291	5.12	2.24
543	Minnesota	Russet Burbank	108	2019-07-23	MN-5	2019	45	9.19	0.93
544	Minnesota	Russet Burbank	108	2019-07-23	MN-5	2019	157	10.09	1.42
545	Minnesota	Russet Burbank	108	2019-07-23	MN-5	2019	247	9.90	1.66
546	Minnesota	Russet Burbank	108	2019-07-23	MN-5	2019	336	8.91	1.96
547	Minnesota	Russet Burbank	108	2019-07-23	MN-5	2019	157	8.63	1.29
548	Minnesota	Russet Burbank	108	2019-07-23	MN-5	2019	247	9.76	1.29
549	Minnesota	Russet Burbank	108	2019-07-23	MN-5	2019	336	9.16	1.27
550	Minnesota	Russet Burbank	108	2019-07-23	MN-5	2019	291	8.69	1.63
551	Minnesota	Russet Burbank	109	2019-08-06	MN-5	2019	45	9.76	0.86
552	Minnesota	Russet Burbank	109	2019-08-06	MN-5	2019	157	11.80	1.36
553	Minnesota	Russet Burbank	109	2019-08-06	MN-5	2019	247	12.73	1.35
554	Minnesota	Russet Burbank	109	2019-08-06	MN-5	2019	336	11.10	1.82
555	Minnesota	Russet Burbank	109	2019-08-06	MN-5	2019	157	9.70	1.09
556	Minnesota	Russet Burbank	109	2019-08-06	MN-5	2019	247	10.87	1.43
557	Minnesota	Russet Burbank	109	2019-08-06	MN-5	2019	336	14.52	1.54
558	Minnesota	Russet Burbank	109	2019-08-06	MN-5	2019	291	12.57	1.69
559	Minnesota	Russet Burbank	110	2019-08-21	MN-5	2019	45	10.92	0.68
560	Minnesota	Russet Burbank	110	2019-08-21	MN-5	2019	157	14.35	0.96
561	Minnesota	Russet Burbank	110	2019-08-21	MN-5	2019	247	13.73	1.17
562	Minnesota	Russet Burbank	110	2019-08-21	MN-5	2019	336	13.59	1.35
563	Minnesota	Russet Burbank	110	2019-08-21	MN-5	2019	157	12.12	0.82
564	Minnesota	Russet Burbank	110	2019-08-21	MN-5	2019	247	13.35	1.17
565	Minnesota	Russet Burbank	110	2019-08-21	MN-5	2019	336	12.42	1.37
566	Minnesota	Russet Burbank	110	2019-08-21	MN-5	2019	291	12.26	1.30
567	Minnesota	Russet Burbank	111	2019-09-16	MN-5	2019	45	10.67	0.86
568	Minnesota	Russet Burbank	111	2019-09-16	MN-5	2019	157	13.39	0.90
569	Minnesota	Russet Burbank	111	2019-09-16	MN-5	2019	247	14.01	1.06
570	Minnesota	Russet Burbank	111	2019-09-16	MN-5	2019	336	13.17	1.05
571	Minnesota	Russet Burbank	111	2019-09-16	MN-5	2019	157	11.63	0.78
572	Minnesota	Russet Burbank	111	2019-09-16	MN-5	2019	247	13.49	1.01
573	Minnesota	Russet Burbank	111	2019-09-16	MN-5	2019	336	11.90	1.16
574	Minnesota	Russet Burbank	111	2019-09-16	MN-5	2019	291	13.22	1.14
575	Minnesota	Clearwater	112	2018-06-26	MN-4	2018	135	1.28	5.09
576	Minnesota	Clearwater	112	2018-06-26	MN-4	2018	269	2.78	4.95
577	Minnesota	Clearwater	112	2018-06-26	MN-4	2018	404	1.20	5.76
578	Minnesota	Clearwater	113	2018-07-10	MN-4	2018	135	3.85	2.36
579	Minnesota	Clearwater	113	2018-07-10	MN-4	2018	269	4.05	3.11
580	Minnesota	Clearwater	113	2018-07-10	MN-4	2018	404	4.16	3.43
581	Minnesota	Clearwater	114	2018-07-18	MN-4	2018	135	4.99	1.70
582	Minnesota	Clearwater	114	2018-07-18	MN-4	2018	269	5.12	2.33
583	Minnesota	Clearwater	114	2018-07-18	MN-4	2018	404	5.65	2.98
584	Minnesota	Clearwater	115	2018-08-01	MN-4	2018	135	6.68	1.24
585	Minnesota	Clearwater	115	2018-08-01	MN-4	2018	269	7.47	1.74
586	Minnesota	Clearwater	115	2018-08-01	MN-4	2018	404	10.18	2.13
587	Minnesota	Clearwater	116	2018-09-13	MN-4	2018	135	11.09	0.97
588	Minnesota	Clearwater	116	2018-09-13	MN-4	2018	269	12.04	1.40
589	Minnesota	Clearwater	116	2018-09-13	MN-4	2018	404	13.48	1.71
590	Minnesota	Clearwater	117	2019-06-26	MN-4	2019	135	1.24	5.96
591	Minnesota	Clearwater	117	2019-06-26	MN-4	2019	269	1.27	5.99
592	Minnesota	Clearwater	117	2019-06-26	MN-4	2019	404	1.22	6.64
593	Minnesota	Clearwater	118	2019-07-11	MN-4	2019	135	3.62	3.09
594	Minnesota	Clearwater	118	2019-07-11	MN-4	2019	269	2.85	3.60
595	Minnesota	Clearwater	118	2019-07-11	MN-4	2019	404	3.33	4.27
596	Minnesota	Clearwater	119	2019-07-24	MN-4	2019	135	4.30	2.06
597	Minnesota	Clearwater	119	2019-07-24	MN-4	2019	269	5.01	2.66
598	Minnesota	Clearwater	119	2019-07-24	MN-4	2019	404	5.19	3.40
599	Minnesota	Clearwater	120	2019-08-07	MN-4	2019	135	7.39	1.56
600	Minnesota	Clearwater	120	2019-08-07	MN-4	2019	269	6.24	2.21
601	Minnesota	Clearwater	120	2019-08-07	MN-4	2019	404	6.53	2.60

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	%N_{Plant} g N 100 g^{-1}
602	Minnesota	Clearwater	121	2019-09-16	MN-4	2019	135	12.15	0.99
603	Minnesota	Clearwater	121	2019-09-16	MN-4	2019	269	11.96	1.04
604	Minnesota	Clearwater	121	2019-09-16	MN-4	2019	404	11.90	1.53
605	Minnesota	Russet Burbank	122	2018-06-26	MN-4	2018	135	3.91	4.38
606	Minnesota	Russet Burbank	122	2018-06-26	MN-4	2018	269	4.50	4.72
607	Minnesota	Russet Burbank	122	2018-06-26	MN-4	2018	404	3.63	4.89
608	Minnesota	Russet Burbank	123	2018-07-10	MN-4	2018	135	7.46	1.97
609	Minnesota	Russet Burbank	123	2018-07-10	MN-4	2018	269	9.40	2.66
610	Minnesota	Russet Burbank	123	2018-07-10	MN-4	2018	404	8.69	2.96
611	Minnesota	Russet Burbank	124	2018-07-18	MN-4	2018	135	8.35	1.56
612	Minnesota	Russet Burbank	124	2018-07-18	MN-4	2018	269	8.32	2.47
613	Minnesota	Russet Burbank	124	2018-07-18	MN-4	2018	404	9.45	2.90
614	Minnesota	Russet Burbank	125	2018-08-01	MN-4	2018	135	13.41	1.31
615	Minnesota	Russet Burbank	125	2018-08-01	MN-4	2018	269	14.63	1.96
616	Minnesota	Russet Burbank	125	2018-08-01	MN-4	2018	404	11.96	2.27
617	Minnesota	Russet Burbank	126	2018-09-13	MN-4	2018	135	15.91	1.06
618	Minnesota	Russet Burbank	126	2018-09-13	MN-4	2018	269	16.70	1.37
619	Minnesota	Russet Burbank	126	2018-09-13	MN-4	2018	404	17.56	1.51
620	Minnesota	Russet Burbank	127	2019-06-26	MN-4	2019	135	2.40	4.84
621	Minnesota	Russet Burbank	127	2019-06-26	MN-4	2019	269	2.24	5.56
622	Minnesota	Russet Burbank	127	2019-06-26	MN-4	2019	404	2.64	5.50
623	Minnesota	Russet Burbank	128	2019-07-11	MN-4	2019	135	5.74	2.53
624	Minnesota	Russet Burbank	128	2019-07-11	MN-4	2019	269	5.70	3.16
625	Minnesota	Russet Burbank	128	2019-07-11	MN-4	2019	404	5.79	3.88
626	Minnesota	Russet Burbank	129	2019-07-24	MN-4	2019	135	8.53	1.72
627	Minnesota	Russet Burbank	129	2019-07-24	MN-4	2019	269	8.01	2.34
628	Minnesota	Russet Burbank	129	2019-07-24	MN-4	2019	404	9.01	2.71
629	Minnesota	Russet Burbank	130	2019-08-07	MN-4	2019	135	12.22	1.42
630	Minnesota	Russet Burbank	130	2019-08-07	MN-4	2019	269	10.84	1.76
631	Minnesota	Russet Burbank	130	2019-08-07	MN-4	2019	404	10.14	2.27
632	Minnesota	Russet Burbank	131	2019-09-16	MN-4	2019	135	13.20	0.96
633	Minnesota	Russet Burbank	131	2019-09-16	MN-4	2019	269	13.32	1.10
634	Minnesota	Russet Burbank	131	2019-09-16	MN-4	2019	404	12.79	1.26
635	Minnesota	Umatilla Russet	132	2018-06-26	MN-4	2018	135	1.85	4.99
636	Minnesota	Umatilla Russet	132	2018-06-26	MN-4	2018	269	1.66	5.48
637	Minnesota	Umatilla Russet	132	2018-06-26	MN-4	2018	404	1.59	5.51
638	Minnesota	Umatilla Russet	133	2018-07-10	MN-4	2018	135	4.33	2.12
639	Minnesota	Umatilla Russet	133	2018-07-10	MN-4	2018	269	6.25	3.24
640	Minnesota	Umatilla Russet	133	2018-07-10	MN-4	2018	404	5.28	3.61
641	Minnesota	Umatilla Russet	134	2018-07-18	MN-4	2018	135	6.29	1.51
642	Minnesota	Umatilla Russet	134	2018-07-18	MN-4	2018	269	7.88	2.15
643	Minnesota	Umatilla Russet	134	2018-07-18	MN-4	2018	404	5.28	2.71
644	Minnesota	Umatilla Russet	135	2018-08-01	MN-4	2018	135	9.27	1.21
645	Minnesota	Umatilla Russet	135	2018-08-01	MN-4	2018	269	8.09	1.77
646	Minnesota	Umatilla Russet	135	2018-08-01	MN-4	2018	404	9.51	2.46
647	Minnesota	Umatilla Russet	136	2018-09-13	MN-4	2018	135	11.84	1.03
648	Minnesota	Umatilla Russet	136	2018-09-13	MN-4	2018	269	14.58	1.32
649	Minnesota	Umatilla Russet	136	2018-09-13	MN-4	2018	404	15.37	1.69
650	Minnesota	Umatilla Russet	137	2019-06-26	MN-4	2019	135	1.70	5.38
651	Minnesota	Umatilla Russet	137	2019-06-26	MN-4	2019	269	1.65	5.83
652	Minnesota	Umatilla Russet	137	2019-06-26	MN-4	2019	404	1.85	6.00
653	Minnesota	Umatilla Russet	138	2019-07-11	MN-4	2019	135	5.25	2.82
654	Minnesota	Umatilla Russet	138	2019-07-11	MN-4	2019	269	5.35	3.32
655	Minnesota	Umatilla Russet	138	2019-07-11	MN-4	2019	404	4.70	4.29
656	Minnesota	Umatilla Russet	139	2019-07-24	MN-4	2019	135	8.27	1.68
657	Minnesota	Umatilla Russet	139	2019-07-24	MN-4	2019	269	8.24	2.20
658	Minnesota	Umatilla Russet	139	2019-07-24	MN-4	2019	404	7.43	3.04
659	Minnesota	Umatilla Russet	140	2019-08-07	MN-4	2019	135	12.42	1.44
660	Minnesota	Umatilla Russet	140	2019-08-07	MN-4	2019	269	10.90	1.87
661	Minnesota	Umatilla Russet	140	2019-08-07	MN-4	2019	404	10.30	2.36
662	Minnesota	Umatilla Russet	141	2019-09-16	MN-4	2019	135	13.65	1.05
663	Minnesota	Umatilla Russet	141	2019-09-16	MN-4	2019	269	13.19	1.18
664	Minnesota	Umatilla Russet	141	2019-09-16	MN-4	2019	404	14.13	1.30
665	Minnesota	Dakota Russet	142	2014-06-30	MN-2	2014	135	1.70	3.56
666	Minnesota	Dakota Russet	142	2014-06-30	MN-2	2014	202	1.70	4.17
667	Minnesota	Dakota Russet	142	2014-06-30	MN-2	2014	269	1.78	4.49
668	Minnesota	Dakota Russet	142	2014-06-30	MN-2	2014	336	2.03	4.28

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	%N_{Plant} g N 100 g^{-1}
669	Minnesota	Dakota Russet	142	2014-06-30	MN-2	2014	404	1.34	5.05
670	Minnesota	Dakota Russet	143	2014-07-15	MN-2	2014	135	5.00	1.77
671	Minnesota	Dakota Russet	143	2014-07-15	MN-2	2014	202	4.98	2.38
672	Minnesota	Dakota Russet	143	2014-07-15	MN-2	2014	269	4.87	2.90
673	Minnesota	Dakota Russet	143	2014-07-15	MN-2	2014	336	4.86	2.94
674	Minnesota	Dakota Russet	143	2014-07-15	MN-2	2014	404	4.61	3.00
675	Minnesota	Dakota Russet	144	2014-07-24	MN-2	2014	135	7.11	1.34
676	Minnesota	Dakota Russet	144	2014-07-24	MN-2	2014	202	7.18	1.61
677	Minnesota	Dakota Russet	144	2014-07-24	MN-2	2014	269	8.02	2.03
678	Minnesota	Dakota Russet	144	2014-07-24	MN-2	2014	336	6.74	2.47
679	Minnesota	Dakota Russet	144	2014-07-24	MN-2	2014	404	7.64	2.53
680	Minnesota	Dakota Russet	145	2014-08-11	MN-2	2014	135	9.50	1.02
681	Minnesota	Dakota Russet	145	2014-08-11	MN-2	2014	202	10.23	1.11
682	Minnesota	Dakota Russet	145	2014-08-11	MN-2	2014	269	9.77	1.48
683	Minnesota	Dakota Russet	145	2014-08-11	MN-2	2014	336	10.36	1.80
684	Minnesota	Dakota Russet	145	2014-08-11	MN-2	2014	404	11.09	1.75
685	Minnesota	Dakota Russet	146	2014-08-26	MN-2	2014	135	10.98	0.94
686	Minnesota	Dakota Russet	146	2014-08-26	MN-2	2014	202	12.29	1.14
687	Minnesota	Dakota Russet	146	2014-08-26	MN-2	2014	269	11.35	1.38
688	Minnesota	Dakota Russet	146	2014-08-26	MN-2	2014	336	13.60	1.51
689	Minnesota	Dakota Russet	146	2014-08-26	MN-2	2014	404	10.73	1.66
690	Minnesota	Dakota Russet	147	2014-09-08	MN-2	2014	135	11.73	0.85
691	Minnesota	Dakota Russet	147	2014-09-08	MN-2	2014	202	12.99	1.10
692	Minnesota	Dakota Russet	147	2014-09-08	MN-2	2014	269	12.60	1.20
693	Minnesota	Dakota Russet	147	2014-09-08	MN-2	2014	336	11.12	1.34
694	Minnesota	Dakota Russet	147	2014-09-08	MN-2	2014	404	10.73	1.52
695	Minnesota	Dakota Russet	148	2014-09-15	MN-2	2014	135	9.94	0.92
696	Minnesota	Dakota Russet	148	2014-09-15	MN-2	2014	202	12.76	1.04
697	Minnesota	Dakota Russet	148	2014-09-15	MN-2	2014	269	13.21	1.19
698	Minnesota	Dakota Russet	148	2014-09-15	MN-2	2014	336	12.78	1.51
699	Minnesota	Dakota Russet	148	2014-09-15	MN-2	2014	404	12.90	1.49
700	Minnesota	Dakota Russet	149	2015-06-23	MN-2	2015	135	2.88	3.15
701	Minnesota	Dakota Russet	149	2015-06-23	MN-2	2015	202	3.60	3.52
702	Minnesota	Dakota Russet	149	2015-06-23	MN-2	2015	269	3.68	4.11
703	Minnesota	Dakota Russet	149	2015-06-23	MN-2	2015	336	3.40	4.01
704	Minnesota	Dakota Russet	149	2015-06-23	MN-2	2015	404	3.49	4.30
705	Minnesota	Dakota Russet	150	2015-07-07	MN-2	2015	135	6.34	1.75
706	Minnesota	Dakota Russet	150	2015-07-07	MN-2	2015	202	6.93	2.07
707	Minnesota	Dakota Russet	150	2015-07-07	MN-2	2015	269	6.75	2.50
708	Minnesota	Dakota Russet	150	2015-07-07	MN-2	2015	336	6.97	2.70
709	Minnesota	Dakota Russet	150	2015-07-07	MN-2	2015	404	6.39	3.20
710	Minnesota	Dakota Russet	151	2015-07-21	MN-2	2015	135	8.86	1.44
711	Minnesota	Dakota Russet	151	2015-07-21	MN-2	2015	202	9.93	1.47
712	Minnesota	Dakota Russet	151	2015-07-21	MN-2	2015	269	9.32	1.91
713	Minnesota	Dakota Russet	151	2015-07-21	MN-2	2015	336	9.78	1.77
714	Minnesota	Dakota Russet	151	2015-07-21	MN-2	2015	404	9.51	2.12
715	Minnesota	Dakota Russet	152	2015-08-04	MN-2	2015	135	14.91	1.02
716	Minnesota	Dakota Russet	152	2015-08-04	MN-2	2015	202	12.90	1.29
717	Minnesota	Dakota Russet	152	2015-08-04	MN-2	2015	269	12.49	1.64
718	Minnesota	Dakota Russet	152	2015-08-04	MN-2	2015	336	13.02	1.74
719	Minnesota	Dakota Russet	152	2015-08-04	MN-2	2015	404	13.06	1.82
720	Minnesota	Dakota Russet	153	2015-08-17	MN-2	2015	135	13.12	1.04
721	Minnesota	Dakota Russet	153	2015-08-17	MN-2	2015	202	12.26	1.15
722	Minnesota	Dakota Russet	153	2015-08-17	MN-2	2015	269	13.51	1.28
723	Minnesota	Dakota Russet	153	2015-08-17	MN-2	2015	336	12.56	1.36
724	Minnesota	Dakota Russet	153	2015-08-17	MN-2	2015	404	12.05	1.42
725	Minnesota	Dakota Russet	154	2015-09-01	MN-2	2015	135	11.94	0.97
726	Minnesota	Dakota Russet	154	2015-09-01	MN-2	2015	202	13.75	1.30
727	Minnesota	Dakota Russet	154	2015-09-01	MN-2	2015	269	12.13	1.38
728	Minnesota	Dakota Russet	154	2015-09-01	MN-2	2015	336	12.68	1.29
729	Minnesota	Dakota Russet	154	2015-09-01	MN-2	2015	404	15.29	1.62
730	Minnesota	Dakota Russet	155	2015-09-16	MN-2	2015	135	14.28	1.04
731	Minnesota	Dakota Russet	155	2015-09-16	MN-2	2015	202	14.59	1.23
732	Minnesota	Dakota Russet	155	2015-09-16	MN-2	2015	269	14.62	1.60
733	Minnesota	Dakota Russet	155	2015-09-16	MN-2	2015	336	14.46	1.55
734	Minnesota	Dakota Russet	155	2015-09-16	MN-2	2015	404	15.44	1.76
735	Minnesota	Easton	156	2014-06-30	MN-2	2014	135	2.03	3.22

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	%N_{Plant} g N 100 g^{-1}
736	Minnesota	Easton	156	2014-06-30	MN-2	2014	202	1.72	4.15
737	Minnesota	Easton	156	2014-06-30	MN-2	2014	269	1.81	3.82
738	Minnesota	Easton	156	2014-06-30	MN-2	2014	336	1.62	4.26
739	Minnesota	Easton	156	2014-06-30	MN-2	2014	404	1.69	4.16
740	Minnesota	Easton	157	2014-07-15	MN-2	2014	135	4.69	1.74
741	Minnesota	Easton	157	2014-07-15	MN-2	2014	202	4.91	2.04
742	Minnesota	Easton	157	2014-07-15	MN-2	2014	269	4.70	2.61
743	Minnesota	Easton	157	2014-07-15	MN-2	2014	336	4.20	2.77
744	Minnesota	Easton	157	2014-07-15	MN-2	2014	404	4.75	3.09
745	Minnesota	Easton	158	2014-07-24	MN-2	2014	135	6.54	1.33
746	Minnesota	Easton	158	2014-07-24	MN-2	2014	202	8.62	1.33
747	Minnesota	Easton	158	2014-07-24	MN-2	2014	269	7.31	1.98
748	Minnesota	Easton	158	2014-07-24	MN-2	2014	336	6.68	2.38
749	Minnesota	Easton	158	2014-07-24	MN-2	2014	404	8.07	2.68
750	Minnesota	Easton	159	2014-08-11	MN-2	2014	135	9.73	0.96
751	Minnesota	Easton	159	2014-08-11	MN-2	2014	202	12.29	1.10
752	Minnesota	Easton	159	2014-08-11	MN-2	2014	269	12.52	1.31
753	Minnesota	Easton	159	2014-08-11	MN-2	2014	336	11.17	1.53
754	Minnesota	Easton	159	2014-08-11	MN-2	2014	404	11.93	1.63
755	Minnesota	Easton	160	2014-08-26	MN-2	2014	135	12.27	0.86
756	Minnesota	Easton	160	2014-08-26	MN-2	2014	202	14.53	0.94
757	Minnesota	Easton	160	2014-08-26	MN-2	2014	269	14.16	1.14
758	Minnesota	Easton	160	2014-08-26	MN-2	2014	336	15.42	1.29
759	Minnesota	Easton	160	2014-08-26	MN-2	2014	404	14.70	1.33
760	Minnesota	Easton	161	2014-09-08	MN-2	2014	135	11.94	0.89
761	Minnesota	Easton	161	2014-09-08	MN-2	2014	202	13.21	0.87
762	Minnesota	Easton	161	2014-09-08	MN-2	2014	269	13.46	0.96
763	Minnesota	Easton	161	2014-09-08	MN-2	2014	336	15.01	1.33
764	Minnesota	Easton	161	2014-09-08	MN-2	2014	404	13.71	1.02
765	Minnesota	Easton	162	2014-09-15	MN-2	2014	135	13.17	0.78
766	Minnesota	Easton	162	2014-09-15	MN-2	2014	202	16.67	0.84
767	Minnesota	Easton	162	2014-09-15	MN-2	2014	269	16.53	1.09
768	Minnesota	Easton	162	2014-09-15	MN-2	2014	336	15.73	1.09
769	Minnesota	Easton	162	2014-09-15	MN-2	2014	404	16.06	1.28
770	Minnesota	Easton	163	2015-06-23	MN-2	2015	135	2.79	3.53
771	Minnesota	Easton	163	2015-06-23	MN-2	2015	202	2.71	4.31
772	Minnesota	Easton	163	2015-06-23	MN-2	2015	269	2.95	4.23
773	Minnesota	Easton	163	2015-06-23	MN-2	2015	336	2.80	4.61
774	Minnesota	Easton	163	2015-06-23	MN-2	2015	404	2.68	4.80
775	Minnesota	Easton	164	2015-07-07	MN-2	2015	135	7.14	1.74
776	Minnesota	Easton	164	2015-07-07	MN-2	2015	202	5.90	2.25
777	Minnesota	Easton	164	2015-07-07	MN-2	2015	269	5.50	2.70
778	Minnesota	Easton	164	2015-07-07	MN-2	2015	336	6.11	3.09
779	Minnesota	Easton	164	2015-07-07	MN-2	2015	404	6.53	3.25
780	Minnesota	Easton	165	2015-07-21	MN-2	2015	135	8.65	1.15
781	Minnesota	Easton	165	2015-07-21	MN-2	2015	202	9.77	1.50
782	Minnesota	Easton	165	2015-07-21	MN-2	2015	269	8.63	1.58
783	Minnesota	Easton	165	2015-07-21	MN-2	2015	336	7.94	2.46
784	Minnesota	Easton	165	2015-07-21	MN-2	2015	404	11.91	2.46
785	Minnesota	Easton	166	2015-08-04	MN-2	2015	135	14.16	1.05
786	Minnesota	Easton	166	2015-08-04	MN-2	2015	202	12.88	1.44
787	Minnesota	Easton	166	2015-08-04	MN-2	2015	269	12.85	1.35
788	Minnesota	Easton	166	2015-08-04	MN-2	2015	336	15.29	1.62
789	Minnesota	Easton	166	2015-08-04	MN-2	2015	404	13.09	1.63
790	Minnesota	Easton	167	2015-08-17	MN-2	2015	135	13.72	0.84
791	Minnesota	Easton	167	2015-08-17	MN-2	2015	202	15.25	0.98
792	Minnesota	Easton	167	2015-08-17	MN-2	2015	269	11.76	1.25
793	Minnesota	Easton	167	2015-08-17	MN-2	2015	336	11.98	1.36
794	Minnesota	Easton	167	2015-08-17	MN-2	2015	404	14.71	1.39
795	Minnesota	Easton	168	2015-09-01	MN-2	2015	135	14.72	0.93
796	Minnesota	Easton	168	2015-09-01	MN-2	2015	202	15.60	1.02
797	Minnesota	Easton	168	2015-09-01	MN-2	2015	269	12.94	1.08
798	Minnesota	Easton	168	2015-09-01	MN-2	2015	336	20.58	1.24
799	Minnesota	Easton	168	2015-09-01	MN-2	2015	404	20.65	1.35
800	Minnesota	Easton	169	2015-09-16	MN-2	2015	135	17.41	0.89
801	Minnesota	Easton	169	2015-09-16	MN-2	2015	202	18.76	1.14
802	Minnesota	Easton	169	2015-09-16	MN-2	2015	269	19.65	1.02

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	%N_{Plant} g N 100 g^{-1}
803	Minnesota	Easton	169	2015-09-16	MN-2	2015	336	22.09	1.27
804	Minnesota	Easton	169	2015-09-16	MN-2	2015	404	20.62	1.43
805	Minnesota	Russet Burbank	170	2014-06-30	MN-2	2014	135	1.93	3.71
806	Minnesota	Russet Burbank	170	2014-06-30	MN-2	2014	202	1.57	4.19
807	Minnesota	Russet Burbank	170	2014-06-30	MN-2	2014	269	1.94	3.19
808	Minnesota	Russet Burbank	170	2014-06-30	MN-2	2014	336	1.88	4.50
809	Minnesota	Russet Burbank	170	2014-06-30	MN-2	2014	404	2.62	3.89
810	Minnesota	Russet Burbank	171	2014-07-15	MN-2	2014	135	5.12	1.85
811	Minnesota	Russet Burbank	171	2014-07-15	MN-2	2014	202	5.10	2.18
812	Minnesota	Russet Burbank	171	2014-07-15	MN-2	2014	269	5.42	2.82
813	Minnesota	Russet Burbank	171	2014-07-15	MN-2	2014	336	5.40	3.39
814	Minnesota	Russet Burbank	171	2014-07-15	MN-2	2014	404	6.83	3.11
815	Minnesota	Russet Burbank	172	2014-07-24	MN-2	2014	135	7.69	1.22
816	Minnesota	Russet Burbank	172	2014-07-24	MN-2	2014	202	9.58	1.51
817	Minnesota	Russet Burbank	172	2014-07-24	MN-2	2014	269	7.45	1.91
818	Minnesota	Russet Burbank	172	2014-07-24	MN-2	2014	336	8.64	2.42
819	Minnesota	Russet Burbank	172	2014-07-24	MN-2	2014	404	7.81	2.71
820	Minnesota	Russet Burbank	173	2014-08-11	MN-2	2014	135	11.95	0.93
821	Minnesota	Russet Burbank	173	2014-08-11	MN-2	2014	202	11.66	1.20
822	Minnesota	Russet Burbank	173	2014-08-11	MN-2	2014	269	12.31	1.37
823	Minnesota	Russet Burbank	173	2014-08-11	MN-2	2014	336	12.03	1.66
824	Minnesota	Russet Burbank	173	2014-08-11	MN-2	2014	404	13.35	2.06
825	Minnesota	Russet Burbank	174	2014-08-26	MN-2	2014	135	12.32	0.82
826	Minnesota	Russet Burbank	174	2014-08-26	MN-2	2014	202	14.35	0.97
827	Minnesota	Russet Burbank	174	2014-08-26	MN-2	2014	269	14.77	1.11
828	Minnesota	Russet Burbank	174	2014-08-26	MN-2	2014	336	13.01	1.32
829	Minnesota	Russet Burbank	174	2014-08-26	MN-2	2014	404	15.55	1.63
830	Minnesota	Russet Burbank	175	2014-09-08	MN-2	2014	135	13.08	0.89
831	Minnesota	Russet Burbank	175	2014-09-08	MN-2	2014	202	16.12	0.87
832	Minnesota	Russet Burbank	175	2014-09-08	MN-2	2014	269	16.37	1.03
833	Minnesota	Russet Burbank	175	2014-09-08	MN-2	2014	336	13.87	1.14
834	Minnesota	Russet Burbank	175	2014-09-08	MN-2	2014	404	14.80	1.16
835	Minnesota	Russet Burbank	176	2014-09-15	MN-2	2014	135	12.12	0.85
836	Minnesota	Russet Burbank	176	2014-09-15	MN-2	2014	202	14.60	0.91
837	Minnesota	Russet Burbank	176	2014-09-15	MN-2	2014	269	14.54	1.05
838	Minnesota	Russet Burbank	176	2014-09-15	MN-2	2014	336	13.78	1.16
839	Minnesota	Russet Burbank	176	2014-09-15	MN-2	2014	404	15.52	1.30
840	Minnesota	Russet Burbank	177	2015-06-23	MN-2	2015	135	3.48	3.10
841	Minnesota	Russet Burbank	177	2015-06-23	MN-2	2015	202	3.82	3.92
842	Minnesota	Russet Burbank	177	2015-06-23	MN-2	2015	269	3.63	3.86
843	Minnesota	Russet Burbank	177	2015-06-23	MN-2	2015	336	3.58	4.47
844	Minnesota	Russet Burbank	177	2015-06-23	MN-2	2015	404	3.86	4.48
845	Minnesota	Russet Burbank	177	2015-06-23	MN-2	2015	135	3.52	3.25
846	Minnesota	Russet Burbank	178	2015-07-07	MN-2	2015	135	7.60	1.78
847	Minnesota	Russet Burbank	178	2015-07-07	MN-2	2015	202	8.70	1.93
848	Minnesota	Russet Burbank	178	2015-07-07	MN-2	2015	269	8.93	2.34
849	Minnesota	Russet Burbank	178	2015-07-07	MN-2	2015	336	7.28	2.87
850	Minnesota	Russet Burbank	178	2015-07-07	MN-2	2015	404	7.49	2.96
851	Minnesota	Russet Burbank	178	2015-07-07	MN-2	2015	135	7.84	1.75
852	Minnesota	Russet Burbank	179	2015-07-21	MN-2	2015	135	10.58	1.09
853	Minnesota	Russet Burbank	179	2015-07-21	MN-2	2015	202	11.74	1.45
854	Minnesota	Russet Burbank	179	2015-07-21	MN-2	2015	269	11.83	1.51
855	Minnesota	Russet Burbank	179	2015-07-21	MN-2	2015	404	9.50	1.66
856	Minnesota	Russet Burbank	179	2015-07-21	MN-2	2015	135	11.58	1.21
857	Minnesota	Russet Burbank	180	2015-08-04	MN-2	2015	135	13.18	1.13
858	Minnesota	Russet Burbank	180	2015-08-04	MN-2	2015	202	14.81	1.29
859	Minnesota	Russet Burbank	180	2015-08-04	MN-2	2015	269	13.21	1.42
860	Minnesota	Russet Burbank	180	2015-08-04	MN-2	2015	336	11.99	1.72
861	Minnesota	Russet Burbank	180	2015-08-04	MN-2	2015	404	15.06	1.74
862	Minnesota	Russet Burbank	180	2015-08-04	MN-2	2015	135	16.78	1.02
863	Minnesota	Russet Burbank	181	2015-08-17	MN-2	2015	135	11.97	0.94
864	Minnesota	Russet Burbank	181	2015-08-17	MN-2	2015	202	13.13	1.36
865	Minnesota	Russet Burbank	181	2015-08-17	MN-2	2015	269	12.29	1.16
866	Minnesota	Russet Burbank	181	2015-08-17	MN-2	2015	336	13.71	1.25
867	Minnesota	Russet Burbank	181	2015-08-17	MN-2	2015	404	15.10	1.41
868	Minnesota	Russet Burbank	181	2015-08-17	MN-2	2015	135	11.22	0.72
869	Minnesota	Russet Burbank	182	2015-09-01	MN-2	2015	135	14.87	0.88

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	%N_{Plant} g N 100 g^{-1}
870	Minnesota	Russet Burbank	182	2015-09-01	MN-2	2015	202	13.36	1.12
871	Minnesota	Russet Burbank	182	2015-09-01	MN-2	2015	269	14.59	1.00
872	Minnesota	Russet Burbank	182	2015-09-01	MN-2	2015	336	15.22	1.22
873	Minnesota	Russet Burbank	182	2015-09-01	MN-2	2015	404	16.70	1.43
874	Minnesota	Russet Burbank	182	2015-09-01	MN-2	2015	135	13.76	0.98
875	Minnesota	Russet Burbank	183	2015-09-16	MN-2	2015	135	16.49	1.09
876	Minnesota	Russet Burbank	183	2015-09-16	MN-2	2015	202	17.34	1.27
877	Minnesota	Russet Burbank	183	2015-09-16	MN-2	2015	269	17.94	1.29
878	Minnesota	Russet Burbank	183	2015-09-16	MN-2	2015	336	18.12	1.41
879	Minnesota	Russet Burbank	183	2015-09-16	MN-2	2015	404	20.49	1.42
880	Minnesota	Russet Burbank	183	2015-09-16	MN-2	2015	135	16.26	1.11
881	Canada	Russet Burbank	186	1997-07-22	Drummond	1997	0	1.20	3.60
882	Canada	Russet Burbank	186	1997-07-22	Drummond	1997	50	1.60	4.00
883	Canada	Russet Burbank	186	1997-07-22	Drummond	1997	100	1.80	4.30
884	Canada	Russet Burbank	186	1997-07-22	Drummond	1997	250	1.70	4.40
885	Canada	Russet Burbank	187	1997-08-01	Drummond	1997	0	2.80	2.70
886	Canada	Russet Burbank	187	1997-08-01	Drummond	1997	50	3.50	2.80
887	Canada	Russet Burbank	187	1997-08-01	Drummond	1997	100	3.70	3.20
888	Canada	Russet Burbank	187	1997-08-01	Drummond	1997	250	4.00	3.20
889	Canada	Russet Burbank	188	1997-08-07	Drummond	1997	0	4.70	2.30
890	Canada	Russet Burbank	188	1997-08-07	Drummond	1997	50	6.90	2.20
891	Canada	Russet Burbank	188	1997-08-07	Drummond	1997	100	6.10	3.00
892	Canada	Russet Burbank	188	1997-08-07	Drummond	1997	250	5.70	3.20
893	Canada	Russet Burbank	189	1997-08-14	Drummond	1997	0	7.50	1.90
894	Canada	Russet Burbank	189	1997-08-14	Drummond	1997	50	7.10	2.20
895	Canada	Russet Burbank	189	1997-08-14	Drummond	1997	100	8.30	2.40
896	Canada	Russet Burbank	189	1997-08-14	Drummond	1997	250	8.40	2.80
897	Canada	Russet Burbank	190	1997-08-21	Drummond	1997	0	8.50	1.40
898	Canada	Russet Burbank	190	1997-08-21	Drummond	1997	50	8.70	1.70
899	Canada	Russet Burbank	190	1997-08-21	Drummond	1997	100	10.30	1.90
900	Canada	Russet Burbank	190	1997-08-21	Drummond	1997	250	8.80	2.40
901	Canada	Russet Burbank	191	1997-08-26	Drummond	1997	0	8.20	1.10
902	Canada	Russet Burbank	191	1997-08-26	Drummond	1997	50	9.70	1.40
903	Canada	Russet Burbank	191	1997-08-26	Drummond	1997	100	9.60	1.80
904	Canada	Russet Burbank	191	1997-08-26	Drummond	1997	250	11.70	2.20
905	Canada	Russet Burbank	192	1997-09-02	Drummond	1997	0	8.80	1.30
906	Canada	Russet Burbank	192	1997-09-02	Drummond	1997	50	10.10	1.50
907	Canada	Russet Burbank	192	1997-09-02	Drummond	1997	100	11.60	2.00
908	Canada	Russet Burbank	192	1997-09-02	Drummond	1997	250	11.90	2.20
909	Canada	Shepody	195	1997-07-15	Drummond	1997	0	1.20	5.50
910	Canada	Shepody	195	1997-07-15	Drummond	1997	50	1.10	6.10
911	Canada	Shepody	195	1997-07-15	Drummond	1997	100	1.30	6.30
912	Canada	Shepody	195	1997-07-15	Drummond	1997	250	1.20	6.30
913	Canada	Shepody	196	1997-07-22	Drummond	1997	0	1.80	3.60
914	Canada	Shepody	196	1997-07-22	Drummond	1997	50	2.10	4.30
915	Canada	Shepody	196	1997-07-22	Drummond	1997	100	2.20	5.10
916	Canada	Shepody	196	1997-07-22	Drummond	1997	250	2.10	5.40
917	Canada	Shepody	197	1997-08-01	Drummond	1997	0	3.20	2.30
918	Canada	Shepody	197	1997-08-01	Drummond	1997	50	5.20	3.00
919	Canada	Shepody	197	1997-08-01	Drummond	1997	100	5.50	3.50
920	Canada	Shepody	197	1997-08-01	Drummond	1997	250	5.60	4.00
921	Canada	Shepody	198	1997-08-07	Drummond	1997	0	5.50	1.80
922	Canada	Shepody	198	1997-08-07	Drummond	1997	50	7.10	2.40
923	Canada	Shepody	198	1997-08-07	Drummond	1997	100	7.30	2.80
924	Canada	Shepody	198	1997-08-07	Drummond	1997	250	5.30	3.60
925	Canada	Shepody	199	1997-08-14	Drummond	1997	0	7.30	1.60
926	Canada	Shepody	199	1997-08-14	Drummond	1997	50	7.30	2.00
927	Canada	Shepody	199	1997-08-14	Drummond	1997	100	6.30	2.80
928	Canada	Shepody	199	1997-08-14	Drummond	1997	250	5.20	3.30
929	Canada	Shepody	200	1997-08-21	Drummond	1997	0	9.40	1.40
930	Canada	Shepody	200	1997-08-21	Drummond	1997	50	10.50	1.80
931	Canada	Shepody	200	1997-08-21	Drummond	1997	100	11.40	1.90
932	Canada	Shepody	200	1997-08-21	Drummond	1997	250	13.50	2.70
933	Canada	Shepody	201	1997-08-26	Drummond	1997	0	9.50	1.10
934	Canada	Shepody	201	1997-08-26	Drummond	1997	50	9.80	1.50
935	Canada	Shepody	201	1997-08-26	Drummond	1997	100	11.50	1.80
936	Canada	Shepody	201	1997-08-26	Drummond	1997	250	11.30	2.40

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	%N_{Plant} g N 100 g^{-1}
937	Canada	Shepody	202	1997-09-02	Drummond	1997	0	7.30	1.30
938	Canada	Shepody	202	1997-09-02	Drummond	1997	50	11.10	1.40
939	Canada	Shepody	202	1997-09-02	Drummond	1997	100	15.40	1.80
940	Canada	Shepody	202	1997-09-02	Drummond	1997	250	13.30	2.50
941	Argentina	Bannock Russet	204	2003-12-23	–	2003	0	3.10	4.20
942	Argentina	Bannock Russet	204	2003-12-23	–	2003	80	3.80	4.20
943	Argentina	Bannock Russet	204	2003-12-23	–	2003	150	4.40	4.20
944	Argentina	Bannock Russet	204	2003-12-23	–	2003	250	4.60	4.40
945	Argentina	Bannock Russet	205	2004-01-07	–	2004	0	4.50	3.20
946	Argentina	Bannock Russet	205	2004-01-07	–	2004	80	6.10	3.40
947	Argentina	Bannock Russet	205	2004-01-07	–	2004	150	6.80	3.60
948	Argentina	Bannock Russet	205	2004-01-07	–	2004	250	7.70	4.20
949	Argentina	Bannock Russet	206	2004-01-22	–	2004	0	4.60	2.80
950	Argentina	Bannock Russet	206	2004-01-22	–	2004	80	6.60	3.10
951	Argentina	Bannock Russet	206	2004-01-22	–	2004	150	8.10	3.00
952	Argentina	Bannock Russet	206	2004-01-22	–	2004	250	11.50	2.90
953	Argentina	Bannock Russet	207	2004-02-11	–	2004	0	6.70	1.90
954	Argentina	Bannock Russet	207	2004-02-11	–	2004	80	8.70	2.10
955	Argentina	Bannock Russet	207	2004-02-11	–	2004	150	9.30	2.20
956	Argentina	Bannock Russet	207	2004-02-11	–	2004	250	11.30	2.50
957	Argentina	Bannock Russet	208	2004-11-28	–	2004	0	2.10	4.30
958	Argentina	Bannock Russet	208	2004-11-28	–	2004	80	2.70	4.40
959	Argentina	Bannock Russet	208	2004-11-28	–	2004	150	2.90	4.70
960	Argentina	Bannock Russet	208	2004-11-28	–	2004	250	3.80	4.50
961	Argentina	Bannock Russet	209	2004-12-04	–	2004	0	3.80	4.10
962	Argentina	Bannock Russet	209	2004-12-04	–	2004	80	5.10	4.20
963	Argentina	Bannock Russet	209	2004-12-04	–	2004	150	5.60	4.20
964	Argentina	Bannock Russet	209	2004-12-04	–	2004	250	6.30	4.30
965	Argentina	Bannock Russet	210	2004-12-26	–	2004	0	7.30	2.40
966	Argentina	Bannock Russet	210	2004-12-26	–	2004	80	12.00	2.80
967	Argentina	Bannock Russet	210	2004-12-26	–	2004	150	16.30	2.90
968	Argentina	Bannock Russet	210	2004-12-26	–	2004	250	19.70	3.40
969	Argentina	Bannock Russet	211	2005-01-22	–	2005	0	13.60	1.30
970	Argentina	Bannock Russet	211	2005-01-22	–	2005	80	15.00	1.40
971	Argentina	Bannock Russet	211	2005-01-22	–	2005	150	17.60	1.40
972	Argentina	Bannock Russet	211	2005-01-22	–	2005	250	20.60	2.10
973	Argentina	Bannock Russet	212	2005-11-16	–	2005	0	2.00	4.80
974	Argentina	Bannock Russet	212	2005-11-16	–	2005	80	2.30	4.90
975	Argentina	Bannock Russet	212	2005-11-16	–	2005	150	2.30	5.00
976	Argentina	Bannock Russet	212	2005-11-16	–	2005	250	2.20	5.30
977	Argentina	Bannock Russet	213	2005-12-01	–	2005	0	3.90	4.00
978	Argentina	Bannock Russet	213	2005-12-01	–	2005	80	4.20	3.90
979	Argentina	Bannock Russet	213	2005-12-01	–	2005	150	4.30	4.10
980	Argentina	Bannock Russet	213	2005-12-01	–	2005	250	5.00	4.60
981	Argentina	Bannock Russet	214	2005-12-14	–	2005	0	7.60	3.20
982	Argentina	Bannock Russet	214	2005-12-14	–	2005	80	8.70	3.20
983	Argentina	Bannock Russet	214	2005-12-14	–	2005	150	8.90	3.40
984	Argentina	Bannock Russet	214	2005-12-14	–	2005	250	12.80	3.50
985	Argentina	Bannock Russet	215	2005-12-30	–	2005	0	13.00	2.20
986	Argentina	Bannock Russet	215	2005-12-30	–	2005	80	18.20	2.40
987	Argentina	Bannock Russet	215	2005-12-30	–	2005	150	23.60	2.50
988	Argentina	Bannock Russet	215	2005-12-30	–	2005	250	25.70	2.70
989	Argentina	Bannock Russet	216	2006-01-13	–	2006	0	20.80	1.60
990	Argentina	Bannock Russet	216	2006-01-13	–	2006	80	24.70	2.00
991	Argentina	Bannock Russet	216	2006-01-13	–	2006	150	32.70	2.40
992	Argentina	Bannock Russet	216	2006-01-13	–	2006	250	36.10	3.10
993	Argentina	Gem Russet	218	2003-12-23	–	2003	0	7.20	3.20
994	Argentina	Gem Russet	218	2003-12-23	–	2003	80	10.30	3.20
995	Argentina	Gem Russet	218	2003-12-23	–	2003	150	13.00	3.00
996	Argentina	Gem Russet	218	2003-12-23	–	2003	250	14.50	3.30
997	Argentina	Gem Russet	219	2004-01-07	–	2004	0	13.70	2.00
998	Argentina	Gem Russet	219	2004-01-07	–	2004	80	17.80	2.20
999	Argentina	Gem Russet	219	2004-01-07	–	2004	150	19.60	2.60
1000	Argentina	Gem Russet	219	2004-01-07	–	2004	250	21.40	2.80
1001	Argentina	Gem Russet	220	2004-01-22	–	2004	0	18.00	1.60
1002	Argentina	Gem Russet	220	2004-01-22	–	2004	80	21.00	2.10
1003	Argentina	Gem Russet	220	2004-01-22	–	2004	150	23.60	2.30

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	$\%N_{Plant}$ g N 100 g^{-1}
1004	Argentina	Gem Russet	220	2004-01-22	–	2004	250	26.30	2.30
1005	Argentina	Gem Russet	221	2004-02-11	–	2004	0	18.30	1.20
1006	Argentina	Gem Russet	221	2004-02-11	–	2004	80	21.30	1.50
1007	Argentina	Gem Russet	221	2004-02-11	–	2004	150	24.30	1.80
1008	Argentina	Gem Russet	221	2004-02-11	–	2004	250	25.90	1.90
1009	Argentina	Gem Russet	222	2004-11-28	–	2004	0	1.70	5.20
1010	Argentina	Gem Russet	222	2004-11-28	–	2004	80	1.90	5.30
1011	Argentina	Gem Russet	222	2004-11-28	–	2004	150	2.20	5.80
1012	Argentina	Gem Russet	222	2004-11-28	–	2004	250	2.20	5.80
1013	Argentina	Gem Russet	223	2004-12-04	–	2004	0	5.30	3.60
1014	Argentina	Gem Russet	223	2004-12-04	–	2004	80	5.60	3.90
1015	Argentina	Gem Russet	223	2004-12-04	–	2004	150	6.40	4.00
1016	Argentina	Gem Russet	223	2004-12-04	–	2004	250	8.00	4.00
1017	Argentina	Gem Russet	224	2004-12-26	–	2004	0	12.70	1.80
1018	Argentina	Gem Russet	224	2004-12-26	–	2004	80	15.90	2.20
1019	Argentina	Gem Russet	224	2004-12-26	–	2004	150	16.30	2.50
1020	Argentina	Gem Russet	224	2004-12-26	–	2004	250	18.40	3.00
1021	Argentina	Gem Russet	225	2005-01-22	–	2005	0	15.80	1.10
1022	Argentina	Gem Russet	225	2005-01-22	–	2005	80	17.40	1.10
1023	Argentina	Gem Russet	225	2005-01-22	–	2005	150	20.50	1.40
1024	Argentina	Gem Russet	225	2005-01-22	–	2005	250	24.60	2.00
1025	Argentina	Gem Russet	226	2005-11-16	–	2005	0	2.00	4.60
1026	Argentina	Gem Russet	226	2005-11-16	–	2005	80	2.00	5.20
1027	Argentina	Gem Russet	226	2005-11-16	–	2005	150	2.10	5.60
1028	Argentina	Gem Russet	226	2005-11-16	–	2005	250	2.10	5.60
1029	Argentina	Gem Russet	227	2005-12-01	–	2005	0	3.80	3.60
1030	Argentina	Gem Russet	227	2005-12-01	–	2005	80	4.20	3.70
1031	Argentina	Gem Russet	227	2005-12-01	–	2005	150	4.90	3.90
1032	Argentina	Gem Russet	227	2005-12-01	–	2005	250	5.90	4.40
1033	Argentina	Gem Russet	228	2005-12-14	–	2005	0	7.50	3.00
1034	Argentina	Gem Russet	228	2005-12-14	–	2005	80	9.10	3.30
1035	Argentina	Gem Russet	228	2005-12-14	–	2005	150	11.30	3.40
1036	Argentina	Gem Russet	228	2005-12-14	–	2005	250	12.10	4.00
1037	Argentina	Gem Russet	229	2005-12-30	–	2005	0	12.70	2.10
1038	Argentina	Gem Russet	229	2005-12-30	–	2005	80	14.00	2.40
1039	Argentina	Gem Russet	229	2005-12-30	–	2005	150	17.80	3.00
1040	Argentina	Gem Russet	229	2005-12-30	–	2005	250	21.50	3.40
1041	Argentina	Gem Russet	230	2006-01-13	–	2006	0	18.00	1.70
1042	Argentina	Gem Russet	230	2006-01-13	–	2006	80	21.90	1.80
1043	Argentina	Gem Russet	230	2006-01-13	–	2006	150	26.60	2.40
1044	Argentina	Gem Russet	230	2006-01-13	–	2006	250	30.20	2.60
1045	Argentina	Gem Russet	231	2006-12-02	–	2006	0	1.30	5.10
1046	Argentina	Gem Russet	231	2006-12-02	–	2006	80	1.30	5.20
1047	Argentina	Gem Russet	231	2006-12-02	–	2006	150	1.30	5.20
1048	Argentina	Gem Russet	231	2006-12-02	–	2006	250	1.60	5.50
1049	Argentina	Gem Russet	232	2006-12-15	–	2006	0	4.10	5.10
1050	Argentina	Gem Russet	232	2006-12-15	–	2006	80	5.10	5.20
1051	Argentina	Gem Russet	232	2006-12-15	–	2006	150	5.30	5.50
1052	Argentina	Gem Russet	232	2006-12-15	–	2006	250	5.40	5.70
1053	Argentina	Gem Russet	233	2006-12-31	–	2006	0	7.50	3.70
1054	Argentina	Gem Russet	233	2006-12-31	–	2006	80	7.90	3.90
1055	Argentina	Gem Russet	233	2006-12-31	–	2006	150	8.80	4.20
1056	Argentina	Gem Russet	233	2006-12-31	–	2006	250	10.10	4.40
1057	Argentina	Gem Russet	234	2007-01-21	–	2007	0	14.30	2.20
1058	Argentina	Gem Russet	234	2007-01-21	–	2007	80	15.40	2.40
1059	Argentina	Gem Russet	234	2007-01-21	–	2007	150	16.50	3.00
1060	Argentina	Gem Russet	234	2007-01-21	–	2007	250	19.20	3.10
1061	Argentina	Gem Russet	235	2007-02-11	–	2007	0	12.00	1.60
1062	Argentina	Gem Russet	235	2007-02-11	–	2007	80	13.60	1.90
1063	Argentina	Gem Russet	235	2007-02-11	–	2007	150	14.20	2.00
1064	Argentina	Gem Russet	235	2007-02-11	–	2007	250	14.90	2.20
1065	Argentina	Innovator	237	2003-12-23	–	2003	0	4.40	2.90
1066	Argentina	Innovator	237	2003-12-23	–	2003	80	4.90	2.80
1067	Argentina	Innovator	237	2003-12-23	–	2003	150	5.60	3.00
1068	Argentina	Innovator	237	2003-12-23	–	2003	250	6.50	3.30
1069	Argentina	Innovator	238	2004-01-07	–	2004	0	6.70	2.40
1070	Argentina	Innovator	238	2004-01-07	–	2004	80	9.50	2.50

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	%N_{Plant} g N 100 g^{-1}
1071	Argentina	Innovator	238	2004-01-07	–	2004	150	10.50	2.50
1072	Argentina	Innovator	238	2004-01-07	–	2004	250	12.90	2.60
1073	Argentina	Innovator	239	2004-01-22	–	2004	0	9.20	1.50
1074	Argentina	Innovator	239	2004-01-22	–	2004	80	11.70	1.60
1075	Argentina	Innovator	239	2004-01-22	–	2004	150	12.40	1.80
1076	Argentina	Innovator	239	2004-01-22	–	2004	250	16.00	2.10
1077	Argentina	Innovator	240	2004-02-11	–	2004	0	15.90	1.10
1078	Argentina	Innovator	240	2004-02-11	–	2004	80	17.20	1.20
1079	Argentina	Innovator	240	2004-02-11	–	2004	150	17.20	1.30
1080	Argentina	Innovator	240	2004-02-11	–	2004	250	22.40	1.40
1081	Argentina	Innovator	241	2004-11-28	–	2004	0	2.40	3.60
1082	Argentina	Innovator	241	2004-11-28	–	2004	80	3.10	3.80
1083	Argentina	Innovator	241	2004-11-28	–	2004	150	3.10	3.90
1084	Argentina	Innovator	241	2004-11-28	–	2004	250	3.20	4.00
1085	Argentina	Innovator	242	2004-12-04	–	2004	0	4.90	2.70
1086	Argentina	Innovator	242	2004-12-04	–	2004	80	5.60	3.10
1087	Argentina	Innovator	242	2004-12-04	–	2004	150	5.90	3.20
1088	Argentina	Innovator	242	2004-12-04	–	2004	250	6.80	3.50
1089	Argentina	Innovator	243	2004-12-26	–	2004	0	9.70	2.30
1090	Argentina	Innovator	243	2004-12-26	–	2004	80	10.80	2.60
1091	Argentina	Innovator	243	2004-12-26	–	2004	150	13.10	2.60
1092	Argentina	Innovator	243	2004-12-26	–	2004	250	15.70	3.00
1093	Argentina	Innovator	244	2005-01-22	–	2005	0	16.80	1.20
1094	Argentina	Innovator	244	2005-01-22	–	2005	80	17.30	1.30
1095	Argentina	Innovator	244	2005-01-22	–	2005	150	19.90	1.50
1096	Argentina	Innovator	244	2005-01-22	–	2005	250	22.60	1.50
1097	Argentina	Innovator	245	2005-11-16	–	2005	0	2.60	4.80
1098	Argentina	Innovator	245	2005-11-16	–	2005	80	2.60	4.70
1099	Argentina	Innovator	245	2005-11-16	–	2005	150	2.70	5.00
1100	Argentina	Innovator	245	2005-11-16	–	2005	250	2.80	5.00
1101	Argentina	Innovator	246	2005-12-01	–	2005	0	4.50	3.20
1102	Argentina	Innovator	246	2005-12-01	–	2005	80	5.30	3.60
1103	Argentina	Innovator	246	2005-12-01	–	2005	150	6.40	3.80
1104	Argentina	Innovator	246	2005-12-01	–	2005	250	7.60	3.80
1105	Argentina	Innovator	247	2005-12-14	–	2005	0	8.00	2.10
1106	Argentina	Innovator	247	2005-12-14	–	2005	80	8.90	2.40
1107	Argentina	Innovator	247	2005-12-14	–	2005	150	11.60	2.80
1108	Argentina	Innovator	247	2005-12-14	–	2005	250	12.90	3.10
1109	Argentina	Innovator	248	2005-12-30	–	2005	0	11.00	1.60
1110	Argentina	Innovator	248	2005-12-30	–	2005	80	12.40	2.00
1111	Argentina	Innovator	248	2005-12-30	–	2005	150	15.10	2.30
1112	Argentina	Innovator	248	2005-12-30	–	2005	250	16.40	2.50
1113	Argentina	Innovator	249	2006-01-13	–	2006	0	16.60	1.00
1114	Argentina	Innovator	249	2006-01-13	–	2006	80	19.40	1.20
1115	Argentina	Innovator	249	2006-01-13	–	2006	150	22.30	1.40
1116	Argentina	Innovator	249	2006-01-13	–	2006	250	24.40	1.50
1117	Argentina	Innovator	250	2006-12-02	–	2006	0	1.10	4.70
1118	Argentina	Innovator	250	2006-12-02	–	2006	80	1.70	4.80
1119	Argentina	Innovator	250	2006-12-02	–	2006	150	2.00	5.10
1120	Argentina	Innovator	250	2006-12-02	–	2006	250	2.40	5.30
1121	Argentina	Innovator	251	2006-12-15	–	2006	0	4.40	3.90
1122	Argentina	Innovator	251	2006-12-15	–	2006	80	4.80	4.30
1123	Argentina	Innovator	251	2006-12-15	–	2006	150	5.00	4.30
1124	Argentina	Innovator	251	2006-12-15	–	2006	250	5.80	4.40
1125	Argentina	Innovator	252	2006-12-31	–	2006	0	7.10	2.70
1126	Argentina	Innovator	252	2006-12-31	–	2006	80	7.40	3.00
1127	Argentina	Innovator	252	2006-12-31	–	2006	150	8.00	3.20
1128	Argentina	Innovator	252	2006-12-31	–	2006	250	9.20	3.40
1129	Argentina	Innovator	253	2007-01-21	–	2007	0	12.50	1.70
1130	Argentina	Innovator	253	2007-01-21	–	2007	80	13.50	2.10
1131	Argentina	Innovator	253	2007-01-21	–	2007	150	13.90	2.40
1132	Argentina	Innovator	253	2007-01-21	–	2007	250	15.20	2.60
1133	Argentina	Innovator	254	2007-02-11	–	2007	0	14.80	1.40
1134	Argentina	Innovator	254	2007-02-11	–	2007	80	15.40	1.50
1135	Argentina	Innovator	254	2007-02-11	–	2007	150	16.80	1.90
1136	Argentina	Innovator	254	2007-02-11	–	2007	250	18.50	2.10
1137	Argentina	Markies Russet	255	2004-11-28	–	2004	0	3.50	4.80

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	%N_{Plant} g N 100 g^{-1}
1138	Argentina	Markies Russet	255	2004-11-28	–	2004	80	3.80	4.90
1139	Argentina	Markies Russet	255	2004-11-28	–	2004	150	4.20	5.10
1140	Argentina	Markies Russet	255	2004-11-28	–	2004	250	4.40	5.40
1141	Argentina	Markies Russet	256	2004-12-04	–	2004	0	5.60	3.60
1142	Argentina	Markies Russet	256	2004-12-04	–	2004	80	6.10	4.00
1143	Argentina	Markies Russet	256	2004-12-04	–	2004	150	7.90	4.20
1144	Argentina	Markies Russet	256	2004-12-04	–	2004	250	8.70	4.10
1145	Argentina	Markies Russet	257	2004-12-26	–	2004	0	10.10	2.70
1146	Argentina	Markies Russet	257	2004-12-26	–	2004	80	11.30	2.80
1147	Argentina	Markies Russet	257	2004-12-26	–	2004	150	13.50	3.00
1148	Argentina	Markies Russet	257	2004-12-26	–	2004	250	16.50	3.20
1149	Argentina	Markies Russet	258	2005-01-22	–	2005	0	11.10	1.80
1150	Argentina	Markies Russet	258	2005-01-22	–	2005	80	13.60	2.20
1151	Argentina	Markies Russet	258	2005-01-22	–	2005	150	16.80	2.40
1152	Argentina	Markies Russet	258	2005-01-22	–	2005	250	18.10	2.60
1153	Argentina	Markies Russet	259	2005-11-16	–	2005	0	1.70	5.00
1154	Argentina	Markies Russet	259	2005-11-16	–	2005	80	1.80	5.60
1155	Argentina	Markies Russet	259	2005-11-16	–	2005	150	1.90	5.60
1156	Argentina	Markies Russet	259	2005-11-16	–	2005	250	1.90	5.60
1157	Argentina	Markies Russet	260	2005-12-01	–	2005	0	4.10	4.30
1158	Argentina	Markies Russet	260	2005-12-01	–	2005	80	4.20	4.40
1159	Argentina	Markies Russet	260	2005-12-01	–	2005	150	4.70	4.50
1160	Argentina	Markies Russet	260	2005-12-01	–	2005	250	5.30	4.40
1161	Argentina	Markies Russet	261	2005-12-14	–	2005	0	8.00	3.10
1162	Argentina	Markies Russet	261	2005-12-14	–	2005	80	8.20	3.30
1163	Argentina	Markies Russet	261	2005-12-14	–	2005	150	9.50	3.40
1164	Argentina	Markies Russet	261	2005-12-14	–	2005	250	11.60	3.70
1165	Argentina	Markies Russet	262	2005-12-30	–	2005	0	12.90	2.30
1166	Argentina	Markies Russet	262	2005-12-30	–	2005	80	14.20	2.60
1167	Argentina	Markies Russet	262	2005-12-30	–	2005	150	16.50	2.80
1168	Argentina	Markies Russet	262	2005-12-30	–	2005	250	19.50	3.00
1169	Argentina	Markies Russet	263	2006-01-13	–	2006	0	14.20	1.70
1170	Argentina	Markies Russet	263	2006-01-13	–	2006	80	19.10	2.10
1171	Argentina	Markies Russet	263	2006-01-13	–	2006	150	23.30	2.30
1172	Argentina	Markies Russet	263	2006-01-13	–	2006	250	23.70	2.50
1173	Argentina	Umatilla Russet	264	2004-11-28	–	2004	0	2.70	3.70
1174	Argentina	Umatilla Russet	264	2004-11-28	–	2004	80	3.00	4.10
1175	Argentina	Umatilla Russet	264	2004-11-28	–	2004	150	3.10	4.20
1176	Argentina	Umatilla Russet	264	2004-11-28	–	2004	250	3.40	4.40
1177	Argentina	Umatilla Russet	265	2004-12-04	–	2004	0	4.30	3.10
1178	Argentina	Umatilla Russet	265	2004-12-04	–	2004	80	6.00	3.40
1179	Argentina	Umatilla Russet	265	2004-12-04	–	2004	150	7.40	3.60
1180	Argentina	Umatilla Russet	265	2004-12-04	–	2004	250	8.10	3.80
1181	Argentina	Umatilla Russet	266	2004-12-26	–	2004	0	11.50	1.90
1182	Argentina	Umatilla Russet	266	2004-12-26	–	2004	80	14.90	2.50
1183	Argentina	Umatilla Russet	266	2004-12-26	–	2004	150	17.60	2.70
1184	Argentina	Umatilla Russet	266	2004-12-26	–	2004	250	22.40	3.30
1185	Argentina	Umatilla Russet	267	2005-01-22	–	2005	0	13.50	0.80
1186	Argentina	Umatilla Russet	267	2005-01-22	–	2005	80	17.20	1.20
1187	Argentina	Umatilla Russet	267	2005-01-22	–	2005	150	23.20	1.40
1188	Argentina	Umatilla Russet	267	2005-01-22	–	2005	250	26.60	1.50
1189	Argentina	Umatilla Russet	268	2005-11-16	–	2005	0	2.10	5.00
1190	Argentina	Umatilla Russet	268	2005-11-16	–	2005	80	2.20	5.50
1191	Argentina	Umatilla Russet	268	2005-11-16	–	2005	150	2.30	5.30
1192	Argentina	Umatilla Russet	268	2005-11-16	–	2005	250	2.40	5.40
1193	Argentina	Umatilla Russet	269	2005-12-01	–	2005	0	3.70	3.50
1194	Argentina	Umatilla Russet	269	2005-12-01	–	2005	80	4.10	3.60
1195	Argentina	Umatilla Russet	269	2005-12-01	–	2005	150	4.40	3.70
1196	Argentina	Umatilla Russet	269	2005-12-01	–	2005	250	6.50	3.70
1197	Argentina	Umatilla Russet	270	2005-12-14	–	2005	0	8.30	2.00
1198	Argentina	Umatilla Russet	270	2005-12-14	–	2005	80	9.80	2.10
1199	Argentina	Umatilla Russet	270	2005-12-14	–	2005	150	10.70	2.50
1200	Argentina	Umatilla Russet	270	2005-12-14	–	2005	250	11.70	3.00
1201	Argentina	Umatilla Russet	271	2005-12-30	–	2005	0	16.10	1.90
1202	Argentina	Umatilla Russet	271	2005-12-30	–	2005	80	18.00	2.10
1203	Argentina	Umatilla Russet	271	2005-12-30	–	2005	150	20.60	2.30
1204	Argentina	Umatilla Russet	271	2005-12-30	–	2005	250	21.70	2.80

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	%N_{Plant} g N 100 g^{-1}
1205	Argentina	Umatilla Russet	272	2006-01-13	–	2006	0	20.40	1.40
1206	Argentina	Umatilla Russet	272	2006-01-13	–	2006	80	21.60	1.60
1207	Argentina	Umatilla Russet	272	2006-01-13	–	2006	150	22.80	1.90
1208	Argentina	Umatilla Russet	272	2006-01-13	–	2006	250	26.20	1.90
1209	Argentina	Umatilla Russet	273	2006-12-02	–	2006	0	1.20	4.60
1210	Argentina	Umatilla Russet	273	2006-12-02	–	2006	80	1.40	4.80
1211	Argentina	Umatilla Russet	273	2006-12-02	–	2006	150	1.50	4.80
1212	Argentina	Umatilla Russet	273	2006-12-02	–	2006	250	1.80	4.90
1213	Argentina	Umatilla Russet	274	2006-12-15	–	2006	0	3.70	4.70
1214	Argentina	Umatilla Russet	274	2006-12-15	–	2006	80	5.00	4.80
1215	Argentina	Umatilla Russet	274	2006-12-15	–	2006	150	6.10	5.20
1216	Argentina	Umatilla Russet	274	2006-12-15	–	2006	250	6.40	5.50
1217	Argentina	Umatilla Russet	275	2006-12-31	–	2006	0	8.20	3.40
1218	Argentina	Umatilla Russet	275	2006-12-31	–	2006	80	10.00	4.00
1219	Argentina	Umatilla Russet	275	2006-12-31	–	2006	150	11.10	4.10
1220	Argentina	Umatilla Russet	275	2006-12-31	–	2006	250	11.90	4.40
1221	Argentina	Umatilla Russet	276	2007-01-21	–	2007	0	10.60	2.10
1222	Argentina	Umatilla Russet	276	2007-01-21	–	2007	80	14.80	2.60
1223	Argentina	Umatilla Russet	276	2007-01-21	–	2007	150	14.90	2.90
1224	Argentina	Umatilla Russet	276	2007-01-21	–	2007	250	16.80	2.90
1225	Argentina	Umatilla Russet	277	2007-02-11	–	2007	0	12.60	1.50
1226	Argentina	Umatilla Russet	277	2007-02-11	–	2007	80	13.30	1.60
1227	Argentina	Umatilla Russet	277	2007-02-11	–	2007	150	16.10	1.80
1228	Argentina	Umatilla Russet	277	2007-02-11	–	2007	250	17.70	2.00
1229	Canada	Russet Burbank	280	1997-07-29	Hartland	1997	0	1.00	3.50
1230	Canada	Russet Burbank	280	1997-07-29	Hartland	1997	50	1.50	3.90
1231	Canada	Russet Burbank	280	1997-07-29	Hartland	1997	100	1.50	4.40
1232	Canada	Russet Burbank	280	1997-07-29	Hartland	1997	250	1.30	4.80
1233	Canada	Russet Burbank	281	1997-08-05	Hartland	1997	0	2.60	2.60
1234	Canada	Russet Burbank	281	1997-08-05	Hartland	1997	50	3.20	3.40
1235	Canada	Russet Burbank	281	1997-08-05	Hartland	1997	100	3.40	3.60
1236	Canada	Russet Burbank	281	1997-08-05	Hartland	1997	250	3.60	3.30
1237	Canada	Russet Burbank	282	1997-08-13	Hartland	1997	0	3.60	1.80
1238	Canada	Russet Burbank	282	1997-08-13	Hartland	1997	50	4.40	2.70
1239	Canada	Russet Burbank	282	1997-08-13	Hartland	1997	100	5.50	2.70
1240	Canada	Russet Burbank	282	1997-08-13	Hartland	1997	250	5.20	2.80
1241	Canada	Russet Burbank	283	1997-08-18	Hartland	1997	0	4.10	1.50
1242	Canada	Russet Burbank	283	1997-08-18	Hartland	1997	50	6.40	2.10
1243	Canada	Russet Burbank	283	1997-08-18	Hartland	1997	100	7.60	2.60
1244	Canada	Russet Burbank	283	1997-08-18	Hartland	1997	250	6.30	2.90
1245	Canada	Russet Burbank	284	1997-08-25	Hartland	1997	0	6.80	1.40
1246	Canada	Russet Burbank	284	1997-08-25	Hartland	1997	50	8.50	2.00
1247	Canada	Russet Burbank	284	1997-08-25	Hartland	1997	100	9.60	2.20
1248	Canada	Russet Burbank	284	1997-08-25	Hartland	1997	250	9.40	2.70
1249	Canada	Russet Burbank	285	1997-09-03	Hartland	1997	0	8.00	1.20
1250	Canada	Russet Burbank	285	1997-09-03	Hartland	1997	50	8.80	1.50
1251	Canada	Russet Burbank	285	1997-09-03	Hartland	1997	100	8.90	1.70
1252	Canada	Russet Burbank	285	1997-09-03	Hartland	1997	250	9.90	2.40
1253	Canada	Russet Burbank	286	1997-09-11	Hartland	1997	0	7.40	1.20
1254	Canada	Russet Burbank	286	1997-09-11	Hartland	1997	50	11.00	1.40
1255	Canada	Russet Burbank	286	1997-09-11	Hartland	1997	100	9.70	1.60
1256	Canada	Russet Burbank	286	1997-09-11	Hartland	1997	250	10.30	1.70
1257	Canada	Shepody	289	1997-07-29	Hartland	1997	0	0.90	4.00
1258	Canada	Shepody	289	1997-07-29	Hartland	1997	50	1.20	4.40
1259	Canada	Shepody	289	1997-07-29	Hartland	1997	100	1.40	5.00
1260	Canada	Shepody	289	1997-07-29	Hartland	1997	250	1.30	5.10
1261	Canada	Shepody	290	1997-08-05	Hartland	1997	0	3.30	2.80
1262	Canada	Shepody	290	1997-08-05	Hartland	1997	50	3.20	3.30
1263	Canada	Shepody	290	1997-08-05	Hartland	1997	100	3.10	3.80
1264	Canada	Shepody	290	1997-08-05	Hartland	1997	250	2.70	4.40
1265	Canada	Shepody	291	1997-08-13	Hartland	1997	0	3.80	2.40
1266	Canada	Shepody	291	1997-08-13	Hartland	1997	50	4.40	2.70
1267	Canada	Shepody	291	1997-08-13	Hartland	1997	100	4.90	3.40
1268	Canada	Shepody	291	1997-08-13	Hartland	1997	250	5.40	3.20
1269	Canada	Shepody	292	1997-08-18	Hartland	1997	0	3.40	1.80
1270	Canada	Shepody	292	1997-08-18	Hartland	1997	50	4.80	2.40
1271	Canada	Shepody	292	1997-08-18	Hartland	1997	100	7.80	2.80

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	$\%N_{Plant}$ g N 100 g^{-1}
1272	Canada	Shepody	292	1997-08-18	Hartland	1997	250	7.00	2.90
1273	Canada	Shepody	293	1997-08-25	Hartland	1997	0	5.60	1.90
1274	Canada	Shepody	293	1997-08-25	Hartland	1997	50	7.30	2.00
1275	Canada	Shepody	293	1997-08-25	Hartland	1997	100	6.40	2.30
1276	Canada	Shepody	293	1997-08-25	Hartland	1997	250	7.90	2.70
1277	Canada	Shepody	294	1997-09-03	Hartland	1997	0	6.10	1.30
1278	Canada	Shepody	294	1997-09-03	Hartland	1997	50	9.00	1.50
1279	Canada	Shepody	294	1997-09-03	Hartland	1997	100	10.60	1.90
1280	Canada	Shepody	294	1997-09-03	Hartland	1997	250	8.50	2.30
1281	Canada	Shepody	295	1997-09-11	Hartland	1997	0	5.90	1.00
1282	Canada	Shepody	295	1997-09-11	Hartland	1997	50	7.90	1.50
1283	Canada	Shepody	295	1997-09-11	Hartland	1997	100	8.20	1.50
1284	Canada	Shepody	295	1997-09-11	Hartland	1997	250	11.30	2.10
1285	Canada	Russet Burbank	298	1995-07-29	Jacksonville	1995	0	1.40	2.90
1286	Canada	Russet Burbank	298	1995-07-29	Jacksonville	1995	50	1.60	3.90
1287	Canada	Russet Burbank	298	1995-07-29	Jacksonville	1995	250	1.70	4.80
1288	Canada	Russet Burbank	299	1995-08-05	Jacksonville	1995	0	1.70	2.70
1289	Canada	Russet Burbank	299	1995-08-05	Jacksonville	1995	50	2.80	3.20
1290	Canada	Russet Burbank	299	1995-08-05	Jacksonville	1995	250	2.20	3.70
1291	Canada	Russet Burbank	300	1995-08-15	Jacksonville	1995	0	3.90	2.00
1292	Canada	Russet Burbank	300	1995-08-15	Jacksonville	1995	50	4.60	2.90
1293	Canada	Russet Burbank	300	1995-08-15	Jacksonville	1995	250	5.20	3.10
1294	Canada	Russet Burbank	301	1995-08-22	Jacksonville	1995	0	5.10	1.80
1295	Canada	Russet Burbank	301	1995-08-22	Jacksonville	1995	50	6.10	2.40
1296	Canada	Russet Burbank	301	1995-08-22	Jacksonville	1995	250	5.70	2.90
1297	Canada	Russet Burbank	302	1995-08-28	Jacksonville	1995	0	5.10	1.80
1298	Canada	Russet Burbank	302	1995-08-28	Jacksonville	1995	50	7.50	2.20
1299	Canada	Russet Burbank	302	1995-08-28	Jacksonville	1995	250	7.20	2.50
1300	Canada	Russet Burbank	303	1995-09-04	Jacksonville	1995	0	8.90	1.70
1301	Canada	Russet Burbank	303	1995-09-04	Jacksonville	1995	50	8.40	1.90
1302	Canada	Russet Burbank	303	1995-09-04	Jacksonville	1995	250	8.70	2.50
1303	Canada	Russet Burbank	304	1995-09-17	Jacksonville	1995	0	10.60	1.40
1304	Canada	Russet Burbank	304	1995-09-17	Jacksonville	1995	50	11.10	1.70
1305	Canada	Russet Burbank	304	1995-09-17	Jacksonville	1995	250	10.20	2.00
1306	Canada	Russet Burbank	305	1995-09-24	Jacksonville	1995	0	10.90	1.30
1307	Canada	Russet Burbank	305	1995-09-24	Jacksonville	1995	50	13.00	1.70
1308	Canada	Russet Burbank	305	1995-09-24	Jacksonville	1995	250	10.20	2.30
1309	Canada	Shepody	308	1995-07-29	Jacksonville	1995	0	1.80	3.40
1310	Canada	Shepody	308	1995-07-29	Jacksonville	1995	50	1.60	4.90
1311	Canada	Shepody	308	1995-07-29	Jacksonville	1995	250	2.00	5.40
1312	Canada	Shepody	309	1995-08-05	Jacksonville	1995	0	2.00	3.40
1313	Canada	Shepody	309	1995-08-05	Jacksonville	1995	50	3.10	3.80
1314	Canada	Shepody	309	1995-08-05	Jacksonville	1995	250	2.70	4.30
1315	Canada	Shepody	310	1995-08-15	Jacksonville	1995	0	4.70	2.30
1316	Canada	Shepody	310	1995-08-15	Jacksonville	1995	50	6.80	2.70
1317	Canada	Shepody	310	1995-08-15	Jacksonville	1995	250	7.60	3.50
1318	Canada	Shepody	311	1995-08-22	Jacksonville	1995	0	4.60	1.90
1319	Canada	Shepody	311	1995-08-22	Jacksonville	1995	50	5.50	2.60
1320	Canada	Shepody	311	1995-08-22	Jacksonville	1995	250	8.10	3.30
1321	Canada	Shepody	312	1995-08-28	Jacksonville	1995	0	7.00	1.80
1322	Canada	Shepody	312	1995-08-28	Jacksonville	1995	50	9.00	2.40
1323	Canada	Shepody	312	1995-08-28	Jacksonville	1995	250	8.20	3.10
1324	Canada	Shepody	313	1995-09-04	Jacksonville	1995	0	7.30	1.60
1325	Canada	Shepody	313	1995-09-04	Jacksonville	1995	50	12.30	2.30
1326	Canada	Shepody	313	1995-09-04	Jacksonville	1995	250	13.10	2.70
1327	Canada	Shepody	314	1995-09-17	Jacksonville	1995	0	9.40	1.30
1328	Canada	Shepody	314	1995-09-17	Jacksonville	1995	50	9.00	1.60
1329	Canada	Shepody	314	1995-09-17	Jacksonville	1995	250	10.00	2.30
1330	Canada	Shepody	315	1995-09-24	Jacksonville	1995	0	8.50	1.10
1331	Canada	Shepody	315	1995-09-24	Jacksonville	1995	50	11.20	1.40
1332	Canada	Shepody	315	1995-09-24	Jacksonville	1995	250	12.50	2.10
1333	Canada	Russet Burbank	318	1995-07-15	London	1995	0	2.00	2.70
1334	Canada	Russet Burbank	318	1995-07-15	London	1995	50	1.00	5.10
1335	Canada	Russet Burbank	318	1995-07-15	London	1995	250	2.00	4.20
1336	Canada	Russet Burbank	319	1995-07-18	London	1995	0	1.80	3.20
1337	Canada	Russet Burbank	319	1995-07-18	London	1995	50	2.70	4.00
1338	Canada	Russet Burbank	319	1995-07-18	London	1995	250	2.80	3.80

	Location	Variety	Index	Date	Study	Year	Rate N kg N ha^{-1}	Biomass Mg ha^{-1}	%N_{Plant} g N 100 g^{-1}
1339	Canada	Russet Burbank	320	1995-07-27	London	1995	0	3.60	1.80
1340	Canada	Russet Burbank	320	1995-07-27	London	1995	50	3.60	3.60
1341	Canada	Russet Burbank	320	1995-07-27	London	1995	250	5.30	3.50
1342	Canada	Russet Burbank	321	1995-08-01	London	1995	0	3.60	1.40
1343	Canada	Russet Burbank	321	1995-08-01	London	1995	50	4.70	2.80
1344	Canada	Russet Burbank	321	1995-08-01	London	1995	250	6.10	2.70
1345	Canada	Russet Burbank	322	1995-08-08	London	1995	0	8.40	1.00
1346	Canada	Russet Burbank	322	1995-08-08	London	1995	50	6.60	2.30
1347	Canada	Russet Burbank	322	1995-08-08	London	1995	250	7.40	2.40
1348	Canada	Russet Burbank	323	1995-08-09	London	1995	0	5.80	1.40
1349	Canada	Russet Burbank	323	1995-08-09	London	1995	50	8.00	2.00
1350	Canada	Russet Burbank	323	1995-08-09	London	1995	250	11.90	2.10
1351	Canada	Russet Burbank	324	1995-08-25	London	1995	0	7.70	0.90
1352	Canada	Russet Burbank	324	1995-08-25	London	1995	50	9.80	1.40
1353	Canada	Russet Burbank	324	1995-08-25	London	1995	250	9.90	2.10
1354	Canada	Russet Burbank	325	1995-09-01	London	1995	0	6.30	0.90
1355	Canada	Russet Burbank	325	1995-09-01	London	1995	50	11.60	1.40
1356	Canada	Russet Burbank	325	1995-09-01	London	1995	250	10.60	1.90
1357	Canada	Shepody	329	1995-07-18	London	1995	0	2.00	3.00
1358	Canada	Shepody	329	1995-07-18	London	1995	50	2.40	4.10
1359	Canada	Shepody	329	1995-07-18	London	1995	250	2.90	4.60
1360	Canada	Shepody	330	1995-07-27	London	1995	0	3.20	1.90
1361	Canada	Shepody	330	1995-07-27	London	1995	50	4.80	3.10
1362	Canada	Shepody	330	1995-07-27	London	1995	250	3.80	4.10
1363	Canada	Shepody	331	1995-08-01	London	1995	0	3.00	1.50
1364	Canada	Shepody	331	1995-08-01	London	1995	50	5.70	2.50
1365	Canada	Shepody	331	1995-08-01	London	1995	250	6.70	3.40
1366	Canada	Shepody	332	1995-08-08	London	1995	0	5.60	1.20
1367	Canada	Shepody	332	1995-08-08	London	1995	50	8.60	2.10
1368	Canada	Shepody	332	1995-08-08	London	1995	250	10.50	3.00
1369	Canada	Shepody	333	1995-08-25	London	1995	0	10.50	1.20
1370	Canada	Shepody	333	1995-08-25	London	1995	50	9.10	1.30
1371	Canada	Shepody	333	1995-08-25	London	1995	250	11.90	1.90
1372	Canada	Shepody	334	1995-09-01	London	1995	0	6.40	0.90
1373	Canada	Shepody	334	1995-09-01	London	1995	50	12.00	1.50
1374	Canada	Shepody	334	1995-09-01	London	1995	250	15.30	2.10
1375	Canada	Shepody	335	1995-09-07	London	1995	0	7.60	0.90
1376	Canada	Shepody	335	1995-09-07	London	1995	50	15.20	1.20
1377	Canada	Shepody	335	1995-09-07	London	1995	250	12.60	1.80

CONCLUSION

SUMMARY OF FINDINGS

Overall, the combined findings of the four chapters of this dissertation provide new insights into the relationships between N and irrigation management strategies and their associated agronomic and environmental outcomes for potato from both an experimental and theoretical standpoint.

EXPERIMENTAL FINDINGS

Remote sensing-based methods demonstrated substantial potential for in-season monitoring of crop N status and management of N fertilizer applications for potato. In the small-plot trial, deficiencies in crop N status were successfully detected using the VIs of MTCI, SR8, and GRVI; however, other VIs such as NDVI and MSAVI2 had minimal sensitivity to detect differences in crop N status. Therefore, structural VIs (i.e., NDVI) should not be used to monitor in-season crop N status and manage N fertilizer applications for potato. Additionally, remote sensing-based methods appear to have the potential to augment or replace conventional methods to monitor crop N status in potato (i.e., petiole nitrate sampling).

Using the NSI approach based on remote sensing, N fertilizer applications were reduced by 8 – 16% without a corresponding reduction in yield. However, the NSI approach has limited potential for future utilization due to the fundamental limitations of the "well-fertilized" reference approach. First, implementing a reference strip or plot can be logistically difficult to do, especially within a production system. Second, and more importantly, “well-fertilized” is a subjective criteria because optimal N rate is both subjective to significant spatial and temporal variability and also cannot be determined prior to implementation of the reference plot. Therefore, alternatives to the NSI approach should be considered to implement for in-season N fertilizer management.

Although the existing N BMPs are effective at mitigation nitrate leaching losses, these practices alone will not be sufficient in all years to meet drinking water quality goals. The findings of this study in the context of previous studies strongly suggest that the development of alternative management practices is needed to further reduce the risk of groundwater contamination. Of the alternative practices considered in this study, remote sensing-based N fertilizer management did not reduce nitrate leaching compared to the N BMPs, while reducing irrigation rate by 15% decreased nitrate leaching load by 17% through a reduction in percolation. Reduced irrigation management has the additional benefit of reducing consumptive water use from groundwater resources. Therefore, improved irrigation management appears to be necessary to further reduce nitrate leaching losses. However, in humid regions, such as Minnesota, the biggest barrier to improving irrigaition management is lack of predicitve accuracy for predicting future weather conditions (e.g., precipitation, evapotranspiration).

THEORETICAL FINDINGS

The commonly stated goal of maximizing NUE will not necessarily achieve desired agronomic and environmental outcomes for potato production, because interpreting NUE requires separate consideration of its constituent factors as well as explicit consideration of

NNI to functionally understand the source of variation (i.e., G x E x M factors). In particular, NUE and NUtE are substantially increased while NUpE and HI are slightly decreased, as crop N status increases (i.e., as NNI decreases). The findings of the present study, in the context of previous studies, indicate implementing management practices that maintain crop N status at an NNI value of 1.0 is one plausible approach to manage the tradeoffs between both agronomic production and losses of N to the environment.

Critical N concentration for potato was found to have meaningful uncertainty in value and significantly vary across G x E interactions. Differences in $\%N_c$ were primarily the result of differences in location (i.e., E), while variety within a given location (i.e., G) had a lesser effect. Resultingly, the computation and consideration of derivative metrics (i.e., NNI) must explicitly account for both this uncertainty and variation due to G x E effects. Additionally, NUE is subject to these same variations due to G x E effects, as a result of the fundamental relationship between NUtE and NNI. Therefore, understanding the source of the G x E effects is essential to improving NUE.

FUTURE RESEARCH OBJECTIVES

There are numerous directions for future research to follow-on from the findings of this dissertation and a summary of the most important objectives to consider is presented below.

REMOTE SENSING

Developing tools for monitoring crop N status and managing in-season N fertilizer applications using remote sensing is critically important. While substantial research into this topic has already been conducted, including within this dissertation, there has yet to be a breakthrough in the practical application of remote sensing to N fertilizer management for on-farm production scenarios. In general, this lack of progress is caused by combination of limitations in agronomic, remote sensing, statistical, and data science methods. Most important, perhaps, is the general failing to recognize precisely what utility remote sensing tools are capable of providing in an agronomic context as well as understanding the limitations of the data available and statistical methods for use in developing algorithms for monitoring crop N status and managing in-season N fertilizer.

Key factors that remain to be addressed include: (1) development of sensors and platforms with high-quality radiometric calibration, appropriate spectral band configuration, high return frequency, high spatial resolution, and low marginal cost per image; (2) development of machine learning algorithms to directly predict key crop N status (e.g., tissue N concentration, etc.) and N response indicators that are not subject to bias due to overfitting on limited training data (i.e., insufficient site-years); and (3) development of machine learning algorithms that are natively appropriate for on-farm applications, including the utilization of on-farm data types and sources, rather than development at the small-plot scale.

Additionally, remote sensing based tools should be used to evaluate variable rate N fertilizer management at the production (i.e., on-farm) scale. It is plausible that with the increased spatial and temporal variability found in soil and weather conditions at this scale relative to small-plot research, variable rate N fertilizer management would both significantly increase yield and significantly reduce N losses to the environment.

Water Quality and Quantity

Identifying management practices that both sufficiently reduce nitrate leaching to meet water quality goals and reduce excessive consumption of surface and groundwater resources for irrigation remain critical goals.

The current paradigm within environmental policy implicitly considers that with sufficient adoption of N fertilizer BMPs, water quality goals will necessarily be achieved. However, this is demonstrably not true as evidenced by the findings of this dissertation. There is still limited understanding of the source and magnitude variation in nitrate leaching losses and residual soil nitrate resulting from non-management factors (e.g., soil, weather, etc.). Further research is necessary to better understand the water quality outcome from N fertilizer BMPs (i.e., combined analysis of multiple experiments) under various environmental conditions.

Additionally, tools to improve irrigation management should continue to be developed to both reduce nitrate leaching losses as well as reduce the consumption of surface water or groundwater supply for agricultural production. In particular, improvements in irrigation management should focus on developing techniques to compute soil moisture balance calculations and monitor soil moisture status across spatial and temporal variability in soil properties, crop growth, and weather. This includes: (1) development of accurate and cost-effective sensors to monitor soil moisture status; (2) software to implement variable rate irrigation technology by computing soil moisture balance calculations, integrating measured soil moisture status, and incorporating high accuracy weather forecasting across spatial and temporal variability found within fields; and (3) evaluation of the agronomic and environmental impacts of adopting improved irrigation management tools.

Finally, research investigating alternative or modified cropping systems designed to mitigate nitrate leaching losses remains necessary. The reductions in nitrate leaching from improved N fertilizer and irrigation management are fundamentally limited by the properties of a given cropping system. Research into this area could include: (1) development of alternative cropping systems as well as adoption of alternative rotation crops such as intermediate wheatgrass; (2) introduction of cover crops into the existing cropping system; or (3) breeding for improved genetics for potato to reduce nitrate leaching losses.

N USE EFFICIENCY

The continued use of NUE as a criteria for evaluating agronomic and environmental outcomes requires: (1) independent consideration of the constituent factors of NUE; and (2) understanding the underlying mechanisms directly related to each constituent factor of NUE. Future research should use the following framework when considering NUE.

In order to reduce potential N losses to the environment, NUpE should be maximized. Accomplishing this objective will require additional research into genetic factors (e.g., rooting system), management practices (e.g., nitrogen and irrigation), and environmental factors (e.g., climate, soil). While this dissertation and substantial previous research has considered the effect of management practices on NUpE, additional research targeted on the interactions between these three factors (i.e., G x E x M) remains necessary. In particular, crop breeding efforts to improve the potato root system in which selection is made on the basis of an increase in NUpE will directly reduce the potential of N losses to the environment.

In order to reduce plant N uptake required to maximize biomass production, critical NUtE should be reduced, and this goal is directly related to interaction between G x E factors and $\%N_c$. Future research here should further explore the G x E interactions under which the relative proportion of biomass allocated to tubers is increased (i.e., $\%N_c$ is decreased). This explicit connection between G x E factors and crop N requirements is novel, but advancements here could have relatively outsized impacts in reducing the amount of N fertilizer required to produce the same amount of tuber yield (i.e., increase in NUE). Initially, this might consist of a systemic review of existing potato varieties and identifying the G x E interactions that result in the lowest $\%N_c$ (i.e., due to increased proportion of relative biomass allocated to tubers).Subsequently, this might also consist of utilizing reduced $\%N_c$ as a selection criteria for future potato breeding efforts.

Finally, explicit consideration of HI separate from the other constituent factors of NUE remains important in order to appropriately identify the source of variation. Unlike NUpE and NUtE, the effect of management practices (e.g., date of vine termination) has the predominant effect of controlling HI, especially for indeterminate varieties. Therefore, future research should take appropriate care to evaluate the source of variation in HI separate from the other factors that control NUpE and NUtE to appropriately separate the G x E x M interaction controlling overall NUE.

N NUTRITION INDEX

The observance of significant difference in critical N concentration across G x E effects for potato presents future challenges for utilizing the NNI framework. However, this approach still remains the best method available to determine crop N status, both for in-season management and for retrospective analysis.

Future research to derive critical N dilution curves should utilize the hierarchical Bayesian statistical framework whenever possible. This is important for two reasons. First, the conventional statistical method to derive the CNDC is subject to greater inferential bias resulting from biased experimental datasets than the Bayesian hierarchical method. Second, the Bayesian method directly quantifies uncertainty in critical N concentration, which should be used whenever possible in the calculation of derivate metrics (i.e., NNI).

In order to account for the effects of G x E for locations and varieties that have not yet had critical N dilution curves developed, an easy-to-use software platform to implement the hierarchical Bayesian framework to derive critical N concentration should be developed. By leveraging the experimental dataset already accumulated for this dissertation, inference of critical N concentration can be made for a new G x E interaction, even with limited experimental data (e.g., limited site-years, sampling dates, N fertilizer treatments, etc.). New data science tools and scientific computing platforms enable the realization of this future research in a manner that was not recently otherwise possible.

Finally, end-of-season NNI measurements present a unique opportunity to evaluate agronomic and environmental outcomes for both small-plot experiments and producer fields. By collecting a single, representative whole plant sample during a more convenient part of the growing season, NNI can be used as a “scorecard” to rate performance. Future research should further evaluate the feasibility and applicability of using end-of-season NNI as an indicator of agronomic and environmental performance.

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